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**Article**

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*Reference:* Nakhipbekova, Symbat/Baibosynova, Gulzhan et. al. (2020). Analysis of the relationship between energy price changes and stock market indices in developed countries. In: International Journal of Energy Economics and Policy 10 (6), S. 169 - 174.
https://www.econjournals.com/index.php/ijeep/article/download/10048/5433.
doi:10.32479/ijeep.10048.

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2020, 10(6), 169-174.

# Analysis of the Relationship between Energy Price Changes and Stock Market Indices in Developed Countries

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**Received:** 07 June 2020 **Accepted:** 04 September 2020 **DOI:** https://doi.org/10.32479/ijeep.10048

**ABSTRACT**

Oil is an important energy source and basic raw material in the manufacturing process. Therefore, the economies of every country in the world are directly or indirectly dependent on oil. The chain effect of the addiction in question also affects the financial markets. In the study, long-term relationship between energy prices (oil, natural gas and electricity prices) and stock market index for developed countries was analyzed with Multiple Structural Break Panel Cointegration Test. The causality relationship between the variables was examined with Dumitrescu-Hurlin Panel Causality Test. According to the findings of the analysis, it was determined that the series move together in the long term. However, while there was causality between oil prices and natural gas prices in the short term, it was revealed that there was no causality between electricity prices and stock market indices.

**Keywords:** Oil Prices, Natural Gas, Electricity, Stock Market İndex, Panel Data Analysis
**JEL Classifications:** C23, G15, Q40

## 1. INTRODUCTION

The most important of the financial indicators are stock market indices. Stock markets are indicators of economic growth and prosperity, reflecting the trust of companies and customers in the economy. With the increase in confidence in the economy, the demand for goods that cause intense energy need also increases, which creates direct energy demand (Sadorsky, 2010). Stock market indices, on the one hand, show the development of the financial sector of the country as well as being an indicator of economic performance. The relationship between economic activities and the development of the financial sector is not one-way (Syzdykova, 2018). Research has shown that there are different views on the direction of the relationship between financial indicators and the change in energy price indices. The fact that the relationship between financial indicators and energy price indexes and their differences varies depending on the economic development levels of countries, dependence on energy resources, the structure of economic regimes and other factors makes this issue even more interesting. Understanding the relationship between energy prices and financial indicators in countries with different characteristics in energy dependency, energy resources and development levels will be helpful in understanding the developing energy markets in recent years, by determining whether some of the characteristics that countries have are important in understanding these relations better.

The purpose of this research is to investigate the relationships between stock market indices and energy variables for developed countries that consume a lot of energy. In the study, developed countries that depend on foreign countries for oil imports are discussed. In the study, the relationship between stock market indexes and energy variables, oil, natural gas and electricity, was measured by econometric analysis. The study consists of 3 parts. Following this introductory chapter, the studies in the literature to determine the effects of energy prices on stock indices are included. In the third section, information about the data, method and application used in the study is given and the findings are discussed. In the final section, the main findings of the study are summarized.

## 2. LITERATURE REVIEW

There are many studies to determine the relationship between energy prices, especially oil, natural gas, and stock indices. However, the studies in the literature are predominantly aimed at determining the effect of oil prices on stock prices. The potential of oil price changes to affect the real economy reveals the possibility that the impact may also be reflected in the financial markets. Therefore, there is an interaction between oil prices and stock market performance. This interaction varies depending on the oil dependency ratio of the country, but it is reflected in the changes in the economic parameters caused by oil prices to the capital markets (Syzdykova, 2018). As a result of the studies, different findings regarding the effects of oil and gas prices on stock prices have been reached. Table 1 summarizes the studies on the effects of energy prices on stock markets.

As seen from the literature review; different methods applied for the same countries or country groups and different data ranges have led to different results. This ensures that the issue remains negotiable and up-to-date.

## 3. METHODS AND DATA

In the research, the relationship between the basic stock market indices of European countries and energy variables was tried to be tested by using the panel data analysis method. In the literature survey, oil prices are used as energy prices variable in almost all of the studies. Oil, natural gas and electricity prices variables were used in this study.

In the analysis, unit root tests, followed by panel cointegration test, panel error correction model and finally panel causality tests were applied for the stasis test of the series.

In the study, stock market index data of developed European countries (Austria, Belgium, Czechia, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovakia, Spain, Sweden, Switzerland and the UK) for 2010-2018 period and oil, natural gas, electricity price change rates were used monthly. Oil, natural gas and electricity data are taken from the International Energy Agency (IEA) stock exchange index data from Bloomberg database.

### 3.1. Cross–section Dependence Tests

In his study Breush and Pagan (1980) proposed to test horizontal cross-sectional dependence with the help of the LaGrange multiplier (LM) test, which is based on the correlation coefficients of residual terms in cases $T \rightarrow \infty$ when $N$ is constant. The LaGrange multiplier (LM) test statistic is calculated as follows:

$$LM = T\sum_{\mathrm{i}=1}^{N\text{-}1}\sum_{\mathrm{j}=\mathrm{i}+1}^{N}\hat{\rho}_{\mathrm{ij}}^{2}$$

Where $\hat{\rho}_{ij}^{2}$ is the instantaneous correlation between units $i$ and $j$. The LM test statistics proposed by Breusch and Pagan (1980) yield deviated results in cases where group mean zero and individual averages are different from zero. To eliminate this deviation, Pesaran et al. (2008) developed a new horizontal cross-section dependency test with a centralized average of zero for the case where the time series dimension T received small value.

The corrected LM statistic developed by Pesaran et al. (2008) maintains its consistency even when the horizontal cross-section dependency (CD) test specified in the Pesaran (2004) study is inconsistent. The corrected LM test statistics developed by Pesaran et al. (2008) are defined as follows.

$$LM_{\mathrm{adj}} = \sqrt{\frac{2}{N(N-1)}\sum_{i=1}^{N\text{-}1}\sum_{j=i+1}^{N}\frac{(T-K)\hat{\rho}_{\mathrm{ij}}^{2}-\mu_{\mathrm{T_{ij}}}}{\sigma_{\mathrm{T_{ij}}}}}$$

Pesaran et al (2008) hypotheses in the horizontal cross-section dependence test are as follows, and the $LM_{adj}$ test statistic under the zero hypothesis ($H_0$) has the standard normal distribution for all $T$ and $N \rightarrow \infty$.

$$H_0 : Cov(u_{it}, u_{jt}) = 0 \quad for\ all\ t$$

$$H_1 : Cov(u_{it}, u_{jt}) \neq 0\ for\ all\ t\ and\ i \neq j$$

### 3.2. Panel Unit Root Test

Since the panel data has the time series dimension, it is important to perform stationary test in order to reflect the realistic relationship of the results. Granger and Newbold (1974) showed that using non-stationary time series may encounter a false regression problem. Since then, analyzing the stationarity of the series has become a standard procedure (Syzdykova et al., 2019). Since the series used in the study has a horizontal cross-section dependency, Pesaran (2007) unit root test, which takes this situation into consideration, was applied. Pesaran (2007) proposed the proxy variables method instead of estimating self-inference and factor loadings in cases where horizontal cross-section dependence was detected in his study. This method is called "Horizontal Section Generalized Dickey Fuller (CADF)" since ADF regression is expanded with delayed horizontal section averages. CADF regression is expressed as an equation as follows.

$$\Delta y_{it} = a_i + \rho_i^* y_{i,t-1} + d_0\bar{y}_{t-1} + d_1\Delta\bar{y}_t + \varepsilon_{it}$$

After estimating the CADF regression, the average of the t-statistics of the lagged variable ($CADF_i$) is taken to obtain CIPS statistics.

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i$$

### 3.3. Multi Structural Fracture Panel Cointegration Test

Panel cointegration models are aimed at examining long-term economic relations with macroeconomic and financial data. The test developed by Basher and Westerlund (2009) tests the presence of cointegration relationship between non-stationary series at the level in case of multiple structural breaks in the relation of horizontal cross-section dependence and cointegration. This method allows for up to three structural breaks in the constant term

**Table 1: Studies to determine the relationship between energy price changes and stock market ındices**

| Author | Period-Variables | Country/ Country groups | Methodology | Result |
|---|---|---|---|---|
| Narayan and Smyth (2005) | 1991 - 2003 | 22 OECD member countries | Panel structural Fracture unit root test | Stock prices follow the random walking hypothesis for OECD countries. |
| Regnier (2007) | January 2002 August 2007; monthly data Oil, Gas Price Changes, Interest Rate, Exchange Rate, Volatility in Oil Prices | Euro Area Countries | GARCH (1,1), Dickey Fuller test and Johansen Cointegration | The results show that fluctuations in oil prices have had negative effects on the stock returns of European public institutions while increasing the value of oil and natural gas stocks. |
| Apergis and Miller (2009) | 1981 - 2007 monthly data; global oil production, real economic activity, real oil prices, stock returns | Australia, Canada, France, Germany, Italy, Japan, UK, USA | VAR and VECM Models | Structural shocks that are intrinsically related to changes in oil prices can have significant effects on stock returns. |
| Fayyad and Daly (2011) | Daily data over 2005 to 2010 oil prices and stock returns | GCC countries, United Kingdom and United States | VAR | Their results showed that the predictive power of oil prices for stock returns enhanced after the increase in oil prices during the GFC. In addition, Qatar, the UAE and the United Kingdom were revealed more resistant to oil shocks than the other markets. |
| Jouini (2013) | Weekly data from 2007 to 201; stock markets and sectors, global oil price | Saudi Arabia | VAR-GARCH method | The results indicate the presence of a transmission of oil price volatility to the Saudi stock sectors. The author also mentioned that the industries may not always respond alike to oil price shocks. |
| Lin and Li (2015) | January 1992 - December 2012, monthly data, natural gas and oil prices | USA, European Countries and Japan | Vector Error Correction Model with GARCH | Although European and Japanese gas prices are coincided with Brent oil prices, gas prices in the USA are decoupling due to the liberalization of the market and the increase in the production of rock gas. |
| Narayan and Gupta (2015) | 150 years (1859:10-2013:12) S&P500 index, and WTI spot crude oil price | USA | Westerlund and Narayan (2012, 2014) tests | They find that oil price is a persistent and endogenous predictor variable and that our proposed stock return predictability model is heteroskedastic. The both positive and negative oil price changes are important predictors of US stock returns, with negative changes relatively more important. |
| Peng et al., (2017) | 1993-2007 weekly data; Oil price and stock price | China | DCC model quantile regression | The oil shocks influence synchronicity according to the size of the firm |
| Dogah and Premaratne (2018) | 2007-2016; Oil price and sectoral equity returns | BRICS markets | VAR model and the Random Forest technique | The results confirm that the oil price volatility has a significant negative effect on Basic Materials, Financials and Industrials sectors. |
| Tiwari et al., (2018) | Oil price and sectoral indices | India | quantile regression model | They find that nine sectors offer diversification gain during bull markets and three sectors can be used to hedge oil prices during a bear market. |
| Yun and Yoon, (2019). | WTI, Brent, Dubai oil price change, stock price and volatility of four airlines | China and South Korea. | VAR-GARCH-BEKK model | There is return and volatility spillover effect between crude oil price and the stock prices of airlines. |
| Hamdi et al., (2019) | 2006–2017, oil price changes and stock price | Gulf Cooperation Council (GCC) countries | Quantile regression analysis (QRA) | The contagion and interdependence between the oil price and stock returns sectors are estimated by frequency domain causality. |

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and trend of the cointegration equation. Developed test statistics (Basher and Westerlund, 2009: 511):

$$Z(M) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M_i+1}\sum_{t=T_{ij-1}+1}^{T_{ij}}\left(\frac{S_{it}^2}{(T_{ij}-T_{ij-1})^2\hat{\sigma}_i^2}\right)$$

$$S_{it} = \sum_{s=T_{ij-1}+1}^{t}\hat{W}_{st}$$

$\hat{W}_{it}$ is the remnants vector obtained from an effective estimator like the least altered least squares (OLS) method. $\hat{\sigma}_i^2$ is a long term variance estimator based on a $\hat{W}_{it}$. When $Z(M)$ is simplified by taking the horizontal section averages, it takes the following figure:

$$Z(M)=\sum_{t=T_{ij-1}+1}^{T_{ij}}\left(\frac{S_{it}^{2}}{(T_{ij}-T_{ij-1})^{2}\hat{\sigma}_{i}^{2}}\right)\sim N(0,1)$$

This test statistic obtained shows a standard normal distribution. Test hypotheses: $H_0$: There is a cointegration relationship between series for all horizontal sections. $H_1$: There is no cointegration relationship between series for some horizontal sections. When the probability value of the calculated test is greater than 0.05, $H_0$ is accepted and the cointegration relationship between the series is decided.

### 3.4. Dumitrescu-Hurlin Panel Causality Test

After making long-term coefficient estimates of the variables in the model, Dumitrescu and Hurlin (2012) Panel causality test was used to determine the causal relationships of the variables in the panel data model. This test is the extended version of Granger causality test for heterogeneous panels, which takes into account the cross-sectional dependence. It can also be used in both T> N and N> T (Dumitrescu and Hurlin, 2012). The basic hypothesis in this Test states that "all of the $\beta_i$ is equal to zero" and that there is no causality to Y in X for the whole panel, with another statement stating that there is no homogeneous panel causality. Under the alternative hypothesis, the model is heterogeneous and is valued according to $\beta_i$ units. The alternative hypothesis is that" some of the $\beta_i$ are different from zero". In other words, according to the alternative hypothesis of this test, there may be no causality relationship in some units. In order to test the basic hypothesis, the Wald statistics for the overall panel are obtained by averaging the Wald Test statistics for the causality analysis of each unit.

Furthermore, Dumitrescu and Hurlin (2012) propose the $\tilde{Z}_{N}^{Hnc}$ test statistic with asymptotic distribution when T>N, and the use of the test statistic $(\bar{Z}_{N,})$ with semi-asymptotic distribution when N>T (Syzdykova et al., 2020).

$$\bar{Z}_{N,}=\sqrt{\frac{\mathrm{N}}{2\times\mathrm{K}}\times\frac{(\mathrm{T}-4)}{(\mathrm{T}+\mathrm{K}-2)}}\times\left[\left(\frac{\mathrm{T}-2}{\mathrm{T}}\right)\bar{W}_{N,T}-\mathrm{K}\right]$$

$$\tilde{Z}_{N}^{Hnc}=\sqrt{\frac{\mathrm{N}}{2\times\mathrm{K}}\times\frac{(\mathrm{T}-2\mathrm{K}-5)}{(\mathrm{T}-\mathrm{K}-3)}}\times\left[\left(\frac{\mathrm{T}-2\mathrm{K}-3}{T-2K-1}\right)\bar{W}_{N,T}-\mathrm{K}\right]\underset{N\to\infty}{\to}N(0,1)$$

## 4. RESULTS

In this study, the existence of horizontal cross-section dependence in the cointegration equation was checked by Breusch and Pagan (1980) and Pesaran, Ulah, Yamagata (2008) tests and the results in the Table 2 were obtained.

According to the results in Table 2; $H_0$ hypothesis was rejected at 1% significance level because probability values were <0.05. It was observed that there is a horizontal cross-section dependence in the model. This result shows that a shock occurring in one of the countries used in the study affected other countries as well. Considering that economies are closely related to each other today, it is a realistic approach that one of the countries that make up the panel is affected by the shock coming from one of the countries that make up the panel. In the next stages, while the unit root and cointegration test is done, horizontal cross-section dependency is taken into consideration. In the Table 3, unit root test results for stock indexes, natural gas, electricity and oil price changes are given. This means that the shock effects on the series do not disappear over time. When the first difference of the variables is taken, all statistics are stagnant according to test values, that is, I (1) carries the process.

**Table 2: Cross-sectional dependence test**

| Variables | Breusch and Pagan (1980) LM test | | Pesaran et al. (2008) LM test | |
|---|---|---|---|---|
| | t-statistics | Probability | t-statistics | Probability |
| *Instock* | 752.6 | 0.002 | 361.3 | 0.000 |
| *Inoil* | 284.2 | 0.000 | 124.7 | 0.000 |
| *Ingas* | 476.2 | 0.000 | 221.7 | 0.000 |
| *Inelectric* | 370.1 | 0.000 | 344.8 | 0.000 |

**Table 3: CADF panel unit root test results**

| Variables | Level | | | 1st difference | | |
|---|---|---|---|---|---|---|
| | $\bar{t}$ | $Z[\bar{t}]$ | Probability | $\bar{t}$ | $Z[\bar{t}]$ | Probability |
| *Instock* | −0.879 | 3.021 | 1.002 | −2.230 | −2.805 | 0.004* |
| *Inoil* | −1.334 | 1.231 | 0.904 | −2.095 | −1.482 | 0.006** |
| *Ingas* | −1.982 | 2.310 | 0.997 | −2.580 | −2.209 | 0.009* |
| *Inelectric* | −1.970 | −0.674 | 0.250 | −2.472 | −1.638 | 0.021** |

Fixed term and trend from deterministic components are included in the model. *and **represent significance levels of 1% and 5%, respectively

According to the results of this analysis, since the same degree of stability is determined for the variables, cointegration analysis can be started. In other words, tests with original values will not contain false regression. Table 4 shows the results of Multiple Structural Fracture Panel cointegration test.

Since the cointegration model has a horizontal cross-section dependency, Westerlund (2009) should consider multi-structural break cointegration analysis according to bootstrap values. According to these results, there is a long-term cointegration relationship between energy variables, electricity, natural gas and oil price indices and stock market indices of developed countries. This result is the same as the studies that reached the conclusion that there is a relationship between Energy prices and different stock market indices made before; Wen et al. (2012), Jammazi (2012), Elyasiani et al. (2013), Creti et al. (2013), Chang et al. (2013), Olson and Wohar (2014), Huang et al. (2017).

According to the results of the cointegration relationship between these variables, energy variables and stock market indices are in a long-term equilibrium relationship. However, the existence of this long-term equilibrium relationship does not mean that these variables will not act independently. If the variables act independently, these independent movements will reach equilibrium in the long run and the variables will act in a balanced manner. As a result of the cointegration analysis, the existence of the cointegration relationship will make the error correction estimate to be made meaningful (Table 5). According to these results, the

**Table 4: Multiple structural fracture panel cointegration test**

| Deterministic components | LM Test Statistics | Asymptotic p-value (no cross section) | Decision | Bootstrap p-value | Decision |
|---|---|---|---|---|---|
| Structural fractures not considered | | | | | |
| Intercept | 10.560 | 0.000 | No cointegration | 0.762 | There is cointegration |
| Intercept and trend | 10.844 | 0.000 | No cointegration | 0.001 | No cointegration |
| Considering structural fractures | | | | | |
| Intercept | 13.299 | 0.000 | No cointegration | 0.765 | There is cointegration |
| Intercept and trend | 14.349 | 0.000 | No cointegration | 0.876 | There is cointegration |

In the structural breaking panel cointegration test, probability values were calculated with 1.000 repetitive bootstrap distribution.

**Table 5: Panel error correction coefficients**

| Variables | Coefficient | t-statistic |
|---|---|---|
| *Inoil* | −0.353 | −9.97 (0.000)* |
| *Ingas* | −0.401 | −11.43 (0.000)* |
| *Inelectric* | −0.396 | −11.18 (0.000)* |

**Table 6: Dumitrescu-Hurlin (2012) panel granger causality test results**

| Null hypothesis | Test | Statistics | p-value |
|---|---|---|---|
| *lnoil* ⇏ *instock* | Z-bar | 2.3313 | 0.0198 |
| | Z-bar tilde | 1.5449 | 0.1337 |
| *instock* ⇏ *lnoil* | Z-bar | 0.1292 | 0.0057 |
| | Z-bar tilde | −0.2067 | 0.0051 |
| *instock* ⇏ *lnstock* | Z-bar | 0.4876 | 0.0079 |
| | Z-bar tilde | 0.0783 | 0.2013 |
| *instock* ⇏ *ingas* | Z-bar | 4.1371 | 0.8771 |
| | Z-bar tilde | 2.9813 | 0.2325 |
| *inelectric* ⇏ *instock* | Z-bar | 1.6058 | 0.1097 |
| | Z-bar tilde | 1.0011 | 0.2709 |
| *inelectric* ⇏ *lnelectric* | Z-bar | 4.7978 | 0.2345 |
| | Z-bar tilde | 3.5763 | 0.7651 |

The null hypothesis; "The independent variable is not the Granger cause of the dependent variable."

panel error correction parameter between oil prices and stock market indices in the countries included in the analysis is negative (approx. 0.35) and significant. Accordingly, approximately 35% of the imbalances that occur in a period between the two variables will be corrected in the next period. Panel error correction parameter between electricity prices and stock market indices −0.39; The panel error correction parameter between natural gas prices and stock market indices was found to be −0.40.

Cointegration analysis measures whether there is a relationship between variables. For information about the direction and degree of this relationship, a causality test will be carried out to determine its direction. After obtaining this information, it will be possible to comment on the relationship between the variables in a healthier way. As a result of the cointegration analysis, the existence of the cointegration relationship will make error correction estimation and causality analysis meaningful. A causality test will be carried out to determine the direction of the relationship between the variables.

According to the causality analysis results between all these explanatory variables and stock market index (Table 6); There is bilateral causality between the stock market variable and oil prices. While there is a one-way causality relationship from the natural gas variable to the stock market variable, there is no causality between electricity prices and the stock market variable. Oil prices and natural gas prices are the reason of stock market index for developed countries, which are handled in line with the findings obtained from the empirical study.

## 5. CONCLUSİON

Today, there are many studies in the literature to determine the effect of the change in energy prices on indices and stock returns. The common point of the studies is to investigate the effects of basic energy determinants such as oil and natural gas on indices that may be affected by these variables. From this point of view, in this study, the long-term relationship between oil, natural gas and electricity prices and stock market index was analyzed with Multiple Structural Break Panel Cointegration Test, and the causality relationship between variables was analyzed with Dumitrescu-Hurlin Panel Causality Test.

The findings obtained support that the series act together in the long term. Therefore, it is possible to talk about a long-term balance. Findings obtained in cointegration analysis also support the studies on this subject. In terms of Dumitrescu-Hurlin Panel causality test, there was no causality relationship between oil and gas prices and stock market index, but no causality relationship was found between electricity prices and stock market index. As in previous studies, these relationships are quite complex and have different causal relationships. In addition, the energy security of the countries, the proximity to the raw materials, the energy production capacities of the countries and the differentiation of the energy markets also play a role in these complex relations.

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