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Does Uncertainty Affect Investor Behaviors and Returns in Stock Exchanges? A New Generation Analysis for the US Equity Markets

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Abstract

This study aims to investigate the relationship between uncertainty level in stock exchanges and stock exchange returns. For this purpose, the effects of the US Equity Market Uncertainty Index (EMUI) on the NYSE, the S&P500, the Dow Jones and the Nasdaq100 stock exchange indexes traded in the US are analyzed using a dataset spanning through 1985:M01-2020:M01. In addition, the US Industrial Production Index and the Non-Farm Employment data along with the FED interest rate are included in the analysis as control variables in order to capture the effect of real economic activities and monetary policy on stock exchange returns. Based on the Carrion-i-Silvestre et al. (2009) multiple structural change unit root test, all series are found to follow I(1). The series are also found to be cointegrated according to the result of the Maki (2012) multiple structural variation cointegration test. Long and short-term analyses are performed using the DOLS method. The long-term analysis suggests that an increase in uncertainty in stock markets negatively affects the returns of all four stock exchanges while the NYSE being the most affected one among others. Moreover, an increase in the Industrial Production Index positively affects all four stock exchange while again the NYSE is found to be the index that is affected the most by such an increase. The Non-Agricultural Employment growth also positively affects all stock exchanges with Nasdaq100 technology index bearing the highest impact. Furthermore, increases in interest rates negatively affects all four stock exchanges operating in the US. The results from the short-term analysis implies that an increase in uncertainty in equity markets negatively affects the stock exchanges investigated. However, this negative effect is less for the NYSE and the S&P500 and greater for the Dow Jones and the Nasdaq100 when compared to the effect obtained from the long-term analysis. Lastly, an increase in the Industrial Production Index affects all four stock exchanges positively in the short-term with the NYSE being the most affected index among the four. Causality relations from uncertainties in equity markets towards the stock exchange returns is analyzed by using a time-varying causality method proposed by Li et al. (2016). According to the results, it is observed that causality from uncertainties in stock exchanges are more apparent on the NYSE, the S&P500 and the Dow Jones while it is relatively less on the Nasdaq100. In general, the causality effects from uncertainties in stock exchanges to stock exchange returns increase during periods in which the Federal Reserve has played a more active role in the US monetary policies. **Keywords:** Uncertainty, Equity Market Uncertainty Index (EMUI), Investor Reaction, Behavioral Finance, NYSE, S&P 500, Dow Jones, Nasdaq 100, Structural Break Unit Root Test, Structural Break Cointegration Test, DOLS, Time-varying Causality Test.

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1. Introduction

In financial studies, it has almost become mechanical to perform analysis with certain already presumed financial data available in an economy.

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However, financial figures are also in close interaction with economic and political uncertainties existent in countries or important financial centers as well as with human behavior, economic conjuncture, and future expectations, which should also be taken into account in any financial analyses.

It is worth providing with some historical background on human behavior and finance, first. Adam Smith in his book Moral Sentiments Theory published in 1759 asserts that humans do not only act with the motive of self-interest (homo economicus), but they are also entities who establish relationships with others and nature in order to achieve what they want. According to Smith (1759), people have a desire to be accepted by other people and institutions. Smith (1759) laid the foundations of Behavioral Economics by associating the economic behavior of individuals with human psychology (Diamond and Vartiainen, 2016). In the 20th century, economists such as Irving Fisher (1867-1947), Vilfiredo Pareto (1848-1923) and J. Maynard Keynes (1883-1946) have also contributed greatly to the efforts in understanding the effects of human behavior on economies. Keynes, one of these researchers, made an important contribution to the finance literature by examining the role of psychological factors in irrational (speculative) events observed in financial markets (Schettkat, 2018).

According to the approach developed by Robert Lucas, known as the Lucas Critique, when governments embark on implementing new policies, economists try to predict the effects of these policies on the premise that the existing relations between economic agents will still continue to be the same in future periods. However, new policies initiated by governments cause changes in the existing relations amongst economic agents by affecting households and firms' expectations regarding the functioning of the economy. Therefore, the effects of new economic policies cannot be accurately predicted under the presumption that the current economic structure will not change. In order to accurately predict the effects of a new economic policy, it is also necessary to clearly take into account how a new policy affects expectations and individual behavior of decision-makers. Lucas (1976) states that an econometric analysis would give inadequate results if only the historical data and developing policy suggestions are used under the assumption that people will behave similarly in the future. Thus, expectations and psychological factors must be accounted for in such analyses if one wants to reach more adequate results (Feve, 2015). In the case of financial markets, it is worth investigating the factors affecting the investor psychology such as the level of uncertainty in the stock exchange markets.

Moreover, the foundations of the Rational Expectations Theory were laid by Muth (1961), further developed by Sargent and Wallace (1975) and Lucas (1976) and accepted by economists around the mid-1970s. According to the theory, people make use of all the information they have access when forming their expectations for the future. This, in turn, suggests that macroeconomic analyses should definitely have some microeconomic bases that would take into account individuals' expectations (Guerrien, 1999: 132-133). Therefore, it is very useful and informative to use data related to certain psychological factors that affect economic activities in financial markets.

Behavioral Economics has created the concept of Behavioral Finance over time. Behavioral finance, whose foundations were laid with the study of Kahneman and Tversky (1979), also brought Daniel Kahneman the 2002 Nobel Prize in Economics (Nobel Prize, 2002). Behavioral finance is a field of research that connects changes occurring in markets to irrational behavior of people. Contrary to the Efficient Markets Hypothesis[1], it argues that price changes in stock markets cannot be fully explained by rational means, because there exist many irrational events affecting prices. Therefore, prices in financial markets can only be explained with the help of models that include irrational behaviors and expectations. This approach also hint us to study psychological factors in our financial analysis.

In this context, the current financial analysis includes the US Equity Market Uncertainty Index (EMUI) as an indicator of the psychological situation prevalent in stock exchange markets when examining the determinants of the returns of four major stock exchanges (the NYSE, the S&P500, the Dow Jones and the Nasdaq100) traded in the US. In addition, the Industrial Production Index and the Non-Agricultural Employment data are taken into account as indicators of real economic activities, along with FED interest rates as an indicator of the monetary policies implemented by the Federal Reserve of the US.

As a continuation of the uncertainty index studies initiated by Baker, Bloom and Davis (2016), Baker et al. (2020) have obtained the EMUI series by normalizing the number of articles published in more than 1000 newspapers compiled by Access World New under News Bank and evokes stock market uncertainty with words "uncertain", "uncertainty", "economy", "economic", "equity

[1]Efficient-Market Hypothesis: It is an approach that suggests that the prices of securities traded in a market reflect all available information about that security. This hypothesis assumes that buyers and sellers determine the price and that they can access all available information simultaneously and symmetrically. In this case, the price formed is considered to be the equilibrium price (Bilir, 2018: 146 - 147).

market", "stock market", "equity price" and "stock price" according to the average value of 100 between 1985-2010.

The authors have also revised this index and started to offer its more advanced version as of August 7, 2013. Researchers stated that the new version offers more consistency in the latest data and better fits the measurement applications used in the monthly newspaper-based EPU directory (Baker et al. 2020). As it is seen, EMUI provides a very important data that can be used in finance studies by measuring a psychological factor i.e. the level of uncertainty in the stock market through newspaper news as a common interaction tool. It is predicted that an increase in the EMUI adversely affects the returns of the stock exchanges in the US.

In this study, the effects of the US[2] Equity Market Uncertainty (EMUI) on the NYSE, the S&P500, the Dow Jones and the Nasdaq100 indexes traded in the US for the period 1985:M01-2020:M01 is analyzed using new generation time series methods. Among these stock exchanges, the NYSE is the largest stock market in the world, the S&P500 is the most traced stock exchange in the world (Icon Securities, 2020) and the best indicator of the wide range of US stocks (Finans Webde, 2019), the Dow Jones includes industry-weighted stocks (Tradingview, 2020) and the Nasdaq100 has technology-weighted stocks (GCM, 2020). Thus, the study aims at revealing how uncertainties in stock markets affect returns to different stock exchanges. The findings of the present study is crucial since no previous study has employed the EMUI so far to account for physiological aspect of transactions in stock exchanges. Especially in the Turkish financial literature, there is almost no study using the "Policy Uncertainty" variable. It is hoped that this study will make an important contribution to the Turkish financial literature in terms of introducing these variables to the readers and other researchers.

The rest of the paper is structured as follows: a brief literature review is presented in the second section, a new generation of econometric analysis is carried out and findings are presented in the third section, the last section provides with evaluation of the findings and concludes.

2. Literature Review

Since the economic uncertainty indexes have been constructed relatively newly, the number of studies examining the effects of the uncertainty indexes on stock market returns is scarce. Few studies that have been conducted on this subject, however, is reviewed in a chronological order below.

Lam and Zhang (2014) analyzed the effects of policy uncertainty on international stock markets using data from the 50 developing and 49 developed countries for the period 1995-2006. Measuring the policy uncertainty of countries with the help of the International Country Risk Guide, the researchers found that policy shocks and bureaucratic problems such as government changes significantly affect stock exchanges in 49 countries.

Arouri et al. (2016) analyzed the long-term relationships between economic policy uncertainty and stock markets in the US for the 1900:M01-2014:M01 period. The Industrial Production Index, inflation, unemployment and the difference between the purchase and sale prices of stocks (default spread) data were also included in the model as control variables (additional explanatory variable). It was determined that there are positive relations between increases in Industrial Production Index and stock returns, and negative relations between uncertainties in economic policy and unemployment and stock returns.

Ongan and Gocer (2017) examined the effects of economic policy uncertainty in the US on the S&P500, the Dow Jones and the Nasdaq100 indexes using the linear and nonlinear analysis methods for the period 1985:M10-2016:M12. They found that there were causality relationships from economic policy uncertainties towards stock prices, and this causality effect becomes more evident during the period of 2008-2013 and 2016 onwards.

Gábor-Tóth and Georgarakos (2017) analyzed the effects of uncertainty in economic policies on participation in the stock market for the US using data from 2002-2014. They determined that uncertainty in economic policies had significant negative effects on individuals' expectations about housing acquisition and stock markets. The authors also stated that the uncertainty index in economic policies is similar to the volatility index. This study also analyzed the effects of interest rates on housing demand, and found that this effect is important for people with a lower education levels.

Gao et al. (2019) analyzed the effects of

[2]The chief reasons of performing this study for the US are that Equity Market Uncertainty data is only available for the US and that the US is an important locomotive for the whole world in financial and other economic activities. The developments in the US economy can affect all countries through financial markets that are largely integrated with each other. For this reason, developments in the US economy must be closely monitored. In addition, many domestic financial institutions and investors trade on the US stock exchanges. Therefore, findings obtained in the present study can be utilized as a guide for the investors around the globe.

economic uncertainties on stock returns using the UK's data for the 1996:M01-2015:M12 period through the Time Varying Parameter Factor-Augmented Vector Autoregressive: TVP-FAVAR model. Researchers first determined the sensitivity of stocks to a number of macroeconomic uncertainty indexes and the economic policy uncertainty index. They found that the uncertainty of economic activity and the UK economic policy uncertainty had adequate power to explain stock returns in Britain, while the uncertainty factors of the UK inflation, the EU economic policy and the US economic policy were not priced in stock returns for in the UK.

Gilal (2019), analyzed the relationship between economic policy uncertainty in the US (EPU) and stock returns traded on the Jakarta Stock Exchange using Indonesia data for 2000:M01-2017:M012 period by employing time-varying correlation method based on OLS-based dynamic conditional correlation method. He found that there is a negative conditional correlation between the economic policy uncertainty in the US and stock market returns in Indonesia, so that increases in the uncertainty in the US economy may lead to a decrease in the Indonesia stock market returns.

It can be inferred from the aforementioned studies that indicators such as economic policy uncertainty index (EPU), fear index (VIX) or the level of volatility in the markets have been, but not an index measuring the uncertainty in the equity market (Equity Market Uncertainty Index: EMUI) has been utilized to measure the psychological aspect of the stock exchanges. Thus, this study aims to analyze the effects of uncertainty level in the US equity markets on the NYSE, the S&P500, the Dow Jones and the Nasdaq100 indexes in order to investigate the determinants of stock market returns more accurately. The EMUI series contains greater information than the EPU in terms of measuring the uncertainty level in stock markets, and from VIX in terms of making this measurement through a very common interaction tool i.e. newspaper news. Thus, utilizing EMUI is indeed much more effective in reflecting the effects of uncertainty in equity markets on different stock exchange indexes.

3. Analysis

3.1 Data set

In this study, the US Equity Market Uncertainty Index (EMUI) data and month-end closing price data of the NYSE, the S&P500 (SP), the Dow Jones (DJ) and the Nasdaq100 (ND) indexes traded in the US for the 1985:M01-2020:M01 period are used. In addition, the US Industrial Production Index (IPI) and Non-Farm Employment (Non-Farm-Payrolls: NFP, Million Persons) data along with the interest rate (IR,%) data are used as indicators of real economic activity and the monetary policy implemented in the US. Arouri et al. (2016) and Gilal (2019) is followed when selecting the variables; Ongan and Gocer (2017) is followed when deciding which stock exchanges are used in the analysis.

The EMUI data from Baker, Bloom and Davis (2020)[3], the stock market data from Yahoo (2020), the IPI data from the OECD (2020), the NFP data from the FRBP (2020), and the IR data from Macrotrends (2020) were compiled. IPI data were seasonally adjusted with the Moving Average method, and the NFP data were taken from the data source as seasonally adjusted[4] already. Except for the IR[5], all series were transformed into their natural logarithms to eliminate the outliers and to prevent any possible variance problem.

First of all, the interaction between the equity market uncertainty index (EMUI) and the stock market indexes can be visually examined with the help of Figure 1.

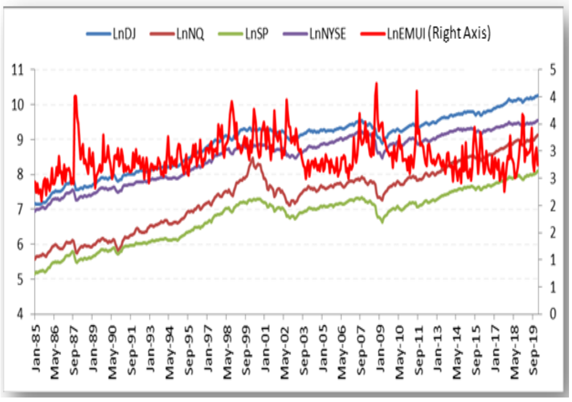

Figure 1. **Interaction Between EMUI and Stock Market Indices**

Source: **Prepared by the author using data from Baker, Bloom and Davis (2020) and Yahoo (2020).**

Note: Ln means the natural logarithm of the series is taken. Data on stock market indices are located on the left axis.

When Figure 1 is analyzed, the first observation that attracts attention is that the stock market

[3] EMUI data Baker et al. (2020) calculated and published daily basis. Since the closing data of the last trading day of each month are used in the analysis, data from the last day of each month are used as EMUI.

[4] Since there is no seasonal effect in other series, no such adjustment has been made.

[5] The reason that the logarithm of the IR series is not taken is that this series also has values that vary in the range of (0,1) and when the logarithm of the numbers in this range is taken, negative values will appear and cause a perception error as if the interest rates are negative in the given country.

indexes decrease compared to an increasing EMU in November 1987, in the October 1997-June 2003 period, in February 2009 and in December 2011. Moreover, the chart shows increased stock market indexes while the EMUI enters into a decreasing trend 2011 onwards. The year 1987 refers to the period of great collapse that started in Hong Kong and influenced the European and the US stock markets. During this period, New Zealand stock market by 60%, Hong Kong stock market by 45.8%, Australian stock market by 41.8%, Spanish stock market by 31%, British stock market by 26.4%, US stock market in average by 22.7% and Canadian stock market fell by 22.5% (Bloomberght, 2016). The South Asian financial crisis in 1997, the Russia's debt crisis in 1998, the terror attacks to the twin towers of the World Trade Organization on 11 September 2001, and the II. Gulf War on 20 March 2003 are thought to be some notable events that coincides with the downward movements in the stock exchanges and the upward movements of the EMUI. Similarly, the 2008 US-based global economic crisis and the fact that the government's borrowing limit was not raised for weeks by the US Congress in 2011 and default risk of the US (DW, 2011) also corresponds with some significant increases in the EMUI. Descriptive statistics of the whole data sample are given in Table 1.

Table. 1. **Descriptive statistics of the sample**

	LnNYSE	LnSP	LnNQ	LnDJ	LnEMUI	LnNIPI	LnNFP	IR
Mean	8.52	6.79	7.38	8.93	2.91	4.40	4.83	3.57
Median	8.76	7.01	7.58	9.22	2.87	4.49	4.87	3.30
Maximum	9.54	8.10	9.13	10.27	4.25	4.67	5.03	9.53
Minimum	6.95	5.15	5.56	7.14	2.08	3.99	4.57	0.07
Std. Dev.	0.70	0.74	0.93	0.80	0.33	0.21	0.12	2.77
Skewness	-0.56	-0.43	-0.23	-0.50	0.86	-0.64	-0.53	0.24
Kurtosis	2.04	2.14	2.04	2.19	4.30	1.90	2.20	1.82
Jarque-Bera	37.65	25.78	19.87	28.98	81.39	50.07	30.60	28.26
Observations	421	421	421	421	421	421	421	421

In Table 1, it can be observed that the data fluctuate around their averages, the difference between the minimum and the maximum values is small, and the standard deviations are quite small. We render from this initial observation that encountering a heteroscedasticity problem in the analysis is not very likely. The data used in the analysis consists of 421 observations, which is a relatively appropriate size for reliable time series estimates. The correlation matrix between the series is given in Table 2.

Table. 2. **Correlation Matrix**

	LnNYSE	LnSP	LnNQ	LnDJ	LnEMUI	LnIPI	LnNFP	IR
LnNYSE	1	0.99	0.98	1.00	0.24	0.99	0.99	-0.74
LnSP	0.99	1	0.99	1.00	0.24	0.97	0.98	-0.71
LnNQ	0.98	0.99	1	0.99	0.21	0.95	0.97	-0.71
LnDJ	1.00	1.00	0.99	1	0.25	0.98	0.99	-0.74
LnEMUI	0.24	0.24	0.21	0.25	1	0.29	0.28	-0.12
LnIPI	0.99	0.97	0.95	0.98	0.29	1	0.98	-0.72
LnNFP	0.99	0.98	0.97	0.99	0.28	0.98	1	-0.72
IR	-0.74	-0.71	-0.71	-0.74	-0.12	-0.72	-0.72	1

According to Table 2, the correlation of the US stock market indexes with the uncertainty level is low (at 0.20s); it is rather high with the Industrial Production Index and Non-Agricultural Employment (at 0.99s), and it is relatively high and negative with the interest rate (at 0.70). This last finding shows that for the US, stocks and time deposits are substitutes. The negative relationship of the interest rate with the IPI and the NFP shows that high interest rates damage investment, production activities and employment in the real sector.

3.2 Model

The present study presents an improvement upon models proposed by Arouri et al. (2016) and Gilal (2019) by adding the NFP series. Consequently, the following four models are constructed for the analysis:

$$\text{Model 1: } LnNYSE_t = \beta_0 + \beta_1 LnEMUI_t + \beta_2 LnIPI_t + \beta_3 LnNFP_t + \beta_4 IR_t + e_t \quad (1)$$

$$\text{Model 2: } LnSP_t = \alpha_0 + \alpha_1 LnEMUI_t + \alpha_2 LnIPI_t + \alpha_3 LnNFP_t + \alpha_4 IR_t + \varepsilon_t \quad (2)$$

$$\text{Model 3: } LnDJ_t = \theta_0 + \theta_1 LnEMUI_t + \theta_2 LnIPI_t + \theta_3 LnNFP_t + \theta_4 IR_t + \epsilon_t \quad (3)$$

$$\text{Model 4: } LnND_t = \gamma_0 + \gamma_1 LnEMUI_t + \gamma_2 LnIPI_t + \gamma_3 LnNFP_t + \gamma_4 IR_t + \vartheta_t \quad (4)$$

In these equations, logarithms of month-end closing prices for each stock exchange are represented by $LnNYSE_t$ for the NYSE, $LnSP_t$ for the S&P500, $LnDJ_t$ for the Dow Jones index and $LnND_t$ for the Nasdaq100 index.

$LnEMUI_t$ is the logarithm of the US Equity Market Uncertainty Index, $LnIPI_t$ is the logarithm of the US Industrial Production Index, $lnNFP_t$ is the logarithm of the number of Non-Farm-Payrolls in the US, and IR_t expresses the interest rate as an indicator of the monetary policies implemented by the Federal Reserve.

e_t, ε_t, ϵ_t and ϑ_t corresponds to error terms that follows a normal distribution with constant variance and zero mean[6].

As a result of estimation of the models, the coefficient of $LnEMU_t$ variable is expected to be negative since increasing uncertainty in stock markets is thought to damage stock market indexes. The coefficient of the IPI_t variable is expected to be positive as it is evaluated that increasing industrial production could possibly turn the real business cycle in the country upwards and this would in turn affect stock markets positively. Similarly, because a rise in Non-Agricultural Employment could increase investment and production activities in the country, and in turn could affect stock markets positively. Thus, the coefficient of NFP_t variable is expected to be positive. Finally, since the time deposit and investing in a stock exchange are considered to be substitutes (alternatives), increasing interest rates could probably decrease stock exchanges. Hence, the coefficient of the IR_t variable is expected to be negative.

3.3 Methodology

In this study, structural breaks are likely to occur in the series since the analysis period is relatively long and there existed many events that had the potential to significantly affect the US economy in respective sub-periods. Therefore, the stationarity of the series is analyzed through Carrion-i-Silvestre et al. (2009) unit root test that allows multiple structural breaks. Also, possible cointegration relationships between the series are tested by Maki (2012) cointegration test that allows multiple structural breaks. Long-term and short-term analyses between the series are performed by using the Dynamic OLS (Dynamic Ordinary Least Squares: DOLS) method since the method is a robust estimator against autocorrelation and heteroscedasticity problems.

Lastly, the causality relationships between the series are examined by the time-varying and nonlinear causality test (LBGC) developed by Li, Balcilar, Gupta and Chang (2016).

3.4 Unit Root Test

Since econometric analysis is sensitive to the stationarity levels of the series used, it is necessary to determine the stationarity of the series by performing unit root tests (Kang, 2014). This, in turn, helps determine the appropriate methods selected further in later stages of the study. To this end, the stationarity levels of the series is tested by the unit root test developed by Carrion-i-Silvestre et al. (2009) that allows multiple structural breaks. In this method, up to five structural breaks are allowed in the series and structural break dates can be determined internally. In addition, the stationarity of the series is handled from five different aspects.

Five different test statistics developed by Carrion-i-Silvestre et al. (2009) are:

$$P_T(\lambda) = \{S(\overline{\alpha},\lambda) - \overline{\alpha}S(1,\lambda)\} / s^2(\lambda) \quad (5)$$

$$MP_T(\lambda) = \left[c^{-2}T^{-2}\sum_{t=-}^{T} y_{t-1}^2 + (1-\overline{c})\,T^{-1}y_T^2\right] / s(\lambda)^2 \quad (6)$$

$$MZ_\alpha(\lambda) = (T^{-1}y_T^2 - s(\lambda)^2)\left(2T^{-2}\sum_{t=-}^{T} y_{t-1}^2\right)^{-1} \quad (7)$$

$$MSB(\lambda) = \left(s(\lambda)^{-2}T^{-2}\sum_{t=-}^{T} y_{t-1}^2\right)^{-1/2} \quad (8)$$

$$MZ_t(\lambda) = (T^{-1}y_T^2 - s(\lambda)^2)\left(4s(\lambda)T^{-2}\sum_{t=-}^{T} y_{t-1}^2\right)^{-1/2} \quad (9)$$

The MZ_α, MZ_t and MSB included in these

[6] *This situation is also called as the White Noise process in the literature.*

models are test statistics that allow multiple structural breaks in the series, and were developed by Ng and Perron (2001) and Perron and Rodriguez (2003). P_T is the optimal point statistics developed by Perron and Rodriguez (2003)? In the models, y_t refers to a series such as $y_t = d_t + u_t$. d_t refers to the deterministic trend, and u_t refers to the term stochastic error. λ refers to the break rate, T refers to the time dimension of the data set, $\bar{c}$ refers to the out-of-center parameter, α expresses the value calculated as $\bar{\alpha} = 1 + \bar{c}/T$, S expresses the minimum value of the $S(\bar{\alpha}, \lambda^0)$ function, and s is the standard deviation derived from the equation $s^2 = (T-k)^{-1} \sum_{t=k+1}^{T} e_{t,k}^2$. In this test, the stationarity of the series is tested through the hypothesis $\alpha = \bar{\alpha}$ and the presence of structural breaks in the series is tested through the hypotheses $\beta_b \neq 0$ and $\tilde{\lambda} = \lambda^0$ (Carrion-i-Silvestre et al., 2009: 1759-1782).

Here the hypotheses of the MZ_α and MZ_t tests:

H_0: $\tilde{\lambda} \neq \lambda^0$ ve $\alpha = 1$. There are no structural breaks and the series is not stationary.

H_1: $\tilde{\lambda} = \lambda^0$ ve $\alpha = \bar{\alpha}$. There are structural breaks and the series is stationary.

Hypotheses of P_T,, MSB and MP_T tests:

H_0: $\tilde{\lambda} = \lambda^0$ ve $\alpha = \bar{\alpha}$. There are structural breaks and the series is stationary.

H_1: $\tilde{\lambda} \neq \lambda^0$ ve $\alpha = 1$ There are no structural breaks and the series is not stationary.

The critical values required to test these hypotheses are obtained with the help of a bootstrap cycle. Results obtained through the Carrion-i-Silvestre et al. (2009) multiple structural change unit root test are presented in Table 3[7].

Table 3. **Unit Root Test Results**

Variable	P_T	MP_T	MZ_α	MSB	MZ_t	Structural Break Dates
LnNYSE	21.33 (8.97)	19.12 (8.97)	-22.09 (-46.67)	0.14 (0.10)	-3.31 (-4.80)	1989:M08; 1994:M10; 1998:M04; 2003:M03; 2008:M09
LnSP	30.99 (9.07)	28.67 (9.07)	-14.71 (-46.16)	0.18 (0.10)	-2.70 (-4.77)	1989:M08; 1993:M02; 1996:M08; 2000:M08; 2008:M09
LnDJ	23.20 (9.56)	21.66 (9.56)	-20.84 (-46.72)	0.15 (0.10)	-3.22 (-4.77)	1989:M07; 1993:M01; 1996:M07; 2001:M09; 2008:M09
LnND	27.89 (9.21)	23.55 (9.21)	-18.68 (-46.88)	0.16 (0.10)	-3.05 (-4.83)	1990:M11; 1994:M12; 2001:M09; 2008:M09; 2016:M02
LnEMUI	14.21 (9.52)	13.84 (6.52)	-19.84 (-47.62)	0.16 (0.10)	-3.74 (-4.86)	1988:M09; 1992:M12; 2002:M07; 2006:M11; 2014:M09
LnIPI	60.62 (9.23)	55.76 (9.23)	-7.75 (-46.78)	0.25 (0.10)	-1.96 (-4.80)	1990:M09; 1996:M01; 2000:M06; 2004:M06; 2008:M09
LnNFP	152.58 (8.94)	145.16 (8.94)	-2.81 (-46.63)	0.41 (0.10)	-1.16 (-4.81)	1988:M06; 1991:M12; 1998:M07; 2008:M07; 2011:M11
IR	104.20 (9.05)	98.34 (9.05)	-4.15 (-46.05)	0.34 (0.10)	-1.42 (-4.76)	1990:M06; 1993:M12; 1997:M08; 2001:M01; 2008:M012
ΔLnNYSE	3.46** (9.53)	3.10** (9.53)	-145.86** (-47.02)	0.05** (0.10)	-8.53** (-4.80)	1990:M07; 1997:M04; 2001:M09; 2005:M02; 2008:M08
ΔLnSP	3.09** (9.52)	2.85** (9.52)	-159.59** (-47.20)	0.05** (0.10)	-8.93** (-4.81)	1990:M07; 1996:M06; 2001:M09; 2005:M05; 2008:M09
ΔLnDJ	3.36** (9.60)	3.13** (9.60)	-145.30** (-47.02)	0.05** (0.10)	-8.52** (-4.80)	1990:M07; 1994:M03; 2001:M09; 2005:M02; 2008:M09
ΔLnND	3.32** (9.51)	3.07** (9.51)	-147.01** (-46.98)	0.05** (0.10)	-8.57** (-4.79)	1990:M07; 1994:M03; 1998:M01; 2001:M09; 2008:M09
ΔLnEMUI	2.66** (9.4)	2.57** (9.64)	-180.89** (-46.96)	0.05** (0.10)	-9.50** (-4.79)	1989:M09; 1997:M09; 2001:M09; 2005:M02; 2008:M08
ΔLnIPI	6.50** (9.17)	6.04** (9.17)	-73.95** (-47.51)	0.08** (0.10)	-6.07** (-4.87)	1989:M06; 1995:M12; 2004:M04; 2008:M08; 2014:M10
ΔLnNFP	4.11** (9.15)	3.68** (9.15)	-119.87** (-47.38)	0.06** (0.10)	-7.73** (-4.84)	1988:M10; 1994:M02; 1999:M01; 2003:M02; 2009:M02
ΔIR	2.74** (9.15)	2.69** (9.15)	-157.01** (-46.11	0.05** (0.10)	-8.85** (-4.75	1988:M10; 1992:M06; 1996:M06; 2000:M05; 2006:M06

Note: Values in parentheses are critical values obtained with 1000 iterative bootstrap cycles (with 5% significance level).

** shows that the related series is stationary at 5% significance level.

[7] For this test, Gauss 10 program and codes written in this programming language by Carrion-i-Silvestre et al. (2009) is used. We are grateful to Josep Lluís Carrion-i-Silvestre for sharing with us the appropriate codes.

According to the results presented in Table 3, all series are found to be stationary in their first differences i.e. I (1). Based on the test results, the Carrion-i-Silvestre et al. (2009) method seems successful in identifying important economic and political developments in the US and the corresponding structural breaks. Among these dates;
- 1988 reflects the effects of the stock market crisis in erupted in 1987,
- 1990 indicates the effects of the First Gulf War,
- The 1995-1996 period reflects the effects of the economic crisis in Mexico,
- 1997 shows the effects of the South Asian financial crisis,
- 2001 reflects the effects of the terrorist attacks experienced on September 11, and
- The year 2008 reflects the impact of the global economic crisis on the markets.

Notwithstanding, it is still necessary to test the existence of any possible cointegration relationship between the series before proceeding with the regression analyses.

3.5 Cointegration Test

When dealing with non-stationary series, it is possible to encounter a spurious regression problem (Granger and Newbold, 1974). When the series to be used in the analysis are not stationary at the level values, a cointegration test should be performed first. When the test results show that the series are co-integrated, the spurious regression problem is not likely to occur (Engle & Grangre, 1987). In this study, since the series are not stationary in their level values, cointegration test should be performed. Engle and Granger (1987) and Johansen (1988) cointegration tests do not take into account structural breaks in the cointegration vector. Structural break cointegration tests developed by Gregory and Hansen (1996), Carrion-i-Silvestre and Sanso (2006) and Westerlund and Edgerton (2006) allow only one structural break in the cointegration vector. However, as the time dimension increases, allowing only one structural break in the cointegration vector becomes insufficient to capture all breaks that have been possibly created by more than one important internal and/or external historical event. It is trivial to see the existence of multiple events within the timespan of our data such as the 1987 stock market crisis, 1990 First Gulf War, September 11, 2001 terrorist attacks, 1995 Mexico, 1997 South Asia, 1998 Russia, 2002 Argentina, and 2008 mortgage crises that had affected the US economy in the period 1985-2020. For this reason, possible cointegration relationships between the series in the study are tested by Maki (2012) structural break unit root test. In this method, up to five structural breaks are allowed in the cointegration vector. Also, the number of structural breaks and the dates of structural breaks are determined internally. The following four different test statistics are used in the method developed by Maki (2012):

- Model 0 allows breaking in the constant term,
- Model 1 allows breaking in the constant term and slope,
- Model 2 is a trend model that allows breaking in the constant term and slope,
- Model 3 allows break in slope and in trend in the constant term.

$$\text{Model 0: } Y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \beta' X_t + u_t \tag{10}$$

$$\text{Model 1: } Y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \beta' X_t + \sum_{i=1}^{k} \beta_i' X_i D_{i,t} + u_t \tag{11}$$

$$\text{Model 2: } Y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \beta' X_t + \sum_{i=1}^{k} \beta_i' X_i D_{i,t} + u_t \tag{12}$$

$$\text{Model 3: } Y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t D_{i,t} + \beta' X_t + \sum_{i=1}^{k} \beta_i' X_i D_{i,t} + u_t \tag{13}$$

Here, t represents the time variable of the study as $t = 1, 2, \dots, T$, Y_t and X_t represent dependent and independent variables following an I(1) process. X_t may be an explanatory variables matrix such as $X_t = (X_{1t}, X_{2t}, \dots, X_{mt})'$. μ refers to the constant term, t refers to the time trend, $D_{i,t}$ refers to the dummy variable that detects structural breaks, and k indicates the number of structural breaks (Maki, 2012, p. 2012). u_t are series of White Noise error terms. This test is the adaptation of Kapetanios (2005) m structural break unit root test to cointegration analysis and determines the existence and history of structural breaks using algorithms employed by Kapetanios (2005) (Maki, 2012, p. 2012). In this test, the existence of cointegration relationship between series is tested with the hypothesis $\rho = 0$ and the presence of structural break in the cointegration vector is tested by the indicator function that only takes a value of 1 or 0.

Maki (2012) hypotheses of structural fracture cointegration test are:

H_0: $\rho = 0$ and indicator function takes the value 0. There are no structural breaks and series are not cointegrated.

H_0: $\rho < 0$ and indicator function takes the value 1. There are structural breaks and series are cointegrated.

The critical values Maki (2012: 2013) required to test these hypotheses are given in Table 1. In this study, the cointegration of the series is tested by Maki (2012)[8] method and the results are shown in Table 4.

Table 4. **Cointegration Test Results**

Analysis Model	Test Model	Test Statistics	Critical Values			Structural Break Dates
			%1	%5	%10	
Model 1	Model 0	-4.92	-6.85	-6.30	-6.03	1991:M12; 1995:M06; 1999:M01
	Model 1	-4.35	-6.55	-6.05	-5.80	1991:M01; 2001:M09
	Model 2	-6.92***	-6.59	-6.01	-5.72	1988:M04; 1991:M05; 1994:M04; 2001:M02
	Model 3	-6.79**	-7.08	-6.52	-6.26	1989:M03; 1996:M02; 2001:M02; 2008:M09
Model 2	Model 0	-5.61**	-5.95	-5.42	-5.13	1988:M01; 1991:M01; 1994:M04; 1997:M04; 2000:M06
	Model 1	-4.59	-5.70	-5.19	-4.93	1991:M01; 2001:M09
	Model 2	-7.40**	-7.47	-6.87	-6.56	1988:M01; 1991:M03; 1996:M01; 2001:M01
	Model 3	-7.92**	-8.21	-7.63	-7.34	1988:M12; 1995:M12; 2001:M09; 2008:M09
Model 3	Model 0	-4.11	-6.30	-5.83	-5.57	1997:M04; 2001:M09
	Model 1	-4.21	-6.55	-6.05	-5.80	1997:M05; 2001:M09
	Model 2	-6.97***	-6.59	-6.01	-5.72	1988:M04; 1992:M02; 1996:M02; 2001:M05
	Model 3	-8.66*	-9.43	-8.87	-8.57	1988:M02; 1993:M02; 2001:M09; 2008:M09
Model 4	Model 0	-5.10	-6.50	-5.99	-5.71	1995:M06; 1998:M08; 2001:M09
	Model 1	-5.95	-6.74	-6.21	-5.97	1991:M12; 1998:M12; 2001:M02
	Model 2	-7.72**	-8.23	-7.62	-7.32	1987:M10; 1991:M01; 1995:M06; 1998:M12
	Model 3	-8.52**	-8.71	-8.12	-7.81	1987:M09; 1991:M01; 1995:M05; 2001:M09; 2008:M08

Note: *, ** and **** indicate the cointegration relationship in the relevant models at the level of 10%, 5% and 1%, respectively

According to the results in Table 4, there is a cointegration relationship between the variables in each model according to at least one test method. Therefore, the spurious regression problem is not likely to be encountered in the regression analysis to be performed for the estimation of the coefficients of the models. This provides evidence that further regression analyses can be reliably conducted. In addition, it is observed that Maki (2012) structural breaking cointegration test successfully identified important events such as the 1987 stock market crisis, the 1990-1991 First Gulf War, the 1995 Mexico crisis, the 1997 South Asian Crisis, the 1998 Russia crisis, the 2001 9/11 terrorist attacks, the 2002 Argentina crisis, and the 2008 global economic crisis. In the cointegration test for each model, the determined structural break dates[9] are included in the long-term analysis with dummy variables. While creating the dummy variables, 1 is assigned to the periods where the relevant structural breaks are present, and 0 to the other periods.

3.6 Long Term Analysis

Since the cointegration relationship between the series is determined, the long-term analyses between the series in each model can be furthered with the DOLS method developed by Stock and Watson (1993). DOLS is a prediction method that is resistant to autocorrelation and heteroscedasticity problems and can be explained simply with the help of Equation (14) as follows:

$$Y_t = \beta_0 + \beta_1 t + \beta_2 X_t + \sum_{i=-m}^{n} \alpha_i \Delta X_{t-i} + \varepsilon_t \quad (14)$$

The notations used in Equation (14) are:

Y_t : Dependent variable, (In this study, LnNYSE_t,

[8] For this calculation, Gauss 10 program and codes written in this programming language are developed by Maki (2012). These codes are received from Daiki Maki via email and we thank them for this contribution

[9] At this stage, the dates determined in Model 3 (the model with a break in a fixed term and a break in a trend) whose cointegration relationship was determined were taken as structural breaking dates.

$LnSP_t$, $LnDJ_t$ and $LnND_t$)
X_t: Independent variables vector, (In this study, $LnEMUI_t$, $LnIPI_t$, $LnNFP_t$ and IR_t)
n: Lag,
m: Lead
The optimal lag and precursor values can be determined with the help of Akaike, Schwarz, information criteria. In this study, DOLS analyses of Equation (1) through Equation (4) are conducted by adding the structural break dummy variables to the respective models. The DOLS estimation results are presented in Table 5.

Table 5. **Long Term Analysis Results**

	Model 1	Model 2	Model 3	Model 4
LnEMUI	-0.32** (0.01)	-0.03* (0.09)	-0.07** (0.01)	-0.06* (0.09)
LnIPI	1.38*** (0.00)	0.40*** (0.00)	0.52*** (0.00)	0.64*** (0.00)
LnNFP	3.64*** (0.00)	6.43*** (0.00)	5.53*** (0.00)	7.33*** (0.00)
IR	-0.004 (0.59)	-0.01*** (0.00)	-0.01*** (0.00)	-0.02** (0.01)
K1987: M09	-	-	-	-0.11*** (0.00)
K1988: M02	-	-	-0.08*** (0.00)	-
K1988: M12	-	-0.43*** (0.00)	-	-
K1989: M03	-3.58 (0.12)	-	-	-
K1991: M01	-	-	-	-0.14*** (0.00)
K1993: M02	-	-	0.02** (0.03)	-
K1995: M05	-	-	-	0.03 (0.12)
K1995: M12	-	-0.01 (0.39)	-	-
K1996: M02	-3.86*** (0.00)	-	-	-
K2001: M02	0.45 (0.81)	-	-	-
K2001: M09	-	-0.05 (0.60)	-0.07*** (0.00)	-0.23*** (0.00)
K2008: M09	6.92** (0.01)	-0.14*** (0.00)	-0.10*** (0.00)	-0.20*** (0.00)
$\mathbf{R^2}$	0.99	0.98	0.98	0.96
$\mathbf{\overline{R}^2}$	0.99	0.98	0.98	0.95
LRV	0.009	0.10	0.10	0.18
SSR	0.25	4.14	4.76	13.90

Note: LRV is Long-Run Variance and SSR is Sum Squared Resid. The low value of these values provides additional evidence that the analysis results are reliable. The values in the parentheses are probability values. *, ** and **** indicate that these coefficients are statistically reliable at the level of 10%, 5%, and 1%, respectively.

According to the results shown in Table 5, increases in uncertainty in the stock markets has negatively affected all four stock exchange indexes. The stock exchange that was affected most by uncertainties is the NYSE. The increase Industrial Production Index has positively affected all four stock exchange indexes, and the most affected stock exchange was the NYSE. The Non-Agricultural Employment growth has also positively affected all stock exchange indexes and the stock exchange bearing the highest impact was the Nasdaq100 technology index. Furthermore, increases in the interest rate have also negatively affected all four stock market indexes in the US. This shows that time deposits are substitutes for investing in stock exchanges in the eyes of the investors. What is interesting here is that the index that was most affected by the changes in the interest rate policies implemented by the FED is the Nasdaq100 technology index.

3.7 Short Term Analysis

The short-term analyses are also conducted using the DOLS method. In the analyses, first order differences of the series and error correction terms (ECT) obtained from the long-term analysis are utilized. Models used in short-term analyses are:

Model 1: $\Delta LnNYSE_t = \beta_0 + \beta_1 \Delta LnEMUI_t + \beta_2 \Delta LnIPI_t + \beta_3 \Delta LnNFP_t + \beta_4 \Delta IR_t + \beta_5 ECT_{1,t-1} + e_t \quad (15)$

Model 2: $\Delta LnSP_t = \alpha_0 + \alpha_1 \Delta LnEMUI_t + \alpha_2 \Delta LnIPI_t + \alpha_3 \Delta LnNFP_t + \alpha_4 \Delta IR_t + \alpha_5 ECT_{2,t-1} + \varepsilon_t \quad (16)$

Model 3: $\Delta LnDJ_t = \theta_0 + \theta_1 \Delta LnEMUI_t + \theta_2 \Delta LnIPI_t + \theta_3 \Delta LnNFP_t + \theta_4 \Delta IR_t + \theta_5 ECT_{3,t-1} + \epsilon_t \quad (17)$

Model 4: $\Delta LnND_t = \gamma_0 + \gamma_1 \Delta LnEMUI_t + \gamma_2 \Delta LnIPI_t + \gamma_3 \Delta LnNFP_t + \gamma_4 \Delta IR_t + \gamma_5 ECT_{4,t-1} + \vartheta_t \quad (18)$

As a result of estimation of the models, it is decided that when the coefficient of ECT is found to be negative and statistically significant, although the deviations is occurring in the short-term among the series, in the long-term the series will act in co-integration and deviations will disappear and the series converges again to equilibrium (Lütkepohl & Kratzig, 2004: 105). This also means that the model's error correction mechanism is working efficiently and the long-term analysis is reliable (Greene, 2002: 654). The results of the short-term analyses obtained through the DOLS method within the framework of the error correction model are presented in Table 6.

Table 6. **Short Term Analysis Results**

	Model 1	Model 2	Model 3	Model 4
$\Delta\mathbf{LnEMUI}$	-0.13*** (0.00)	-0.05*** (0.00)	-0.05*** (0.00)	-0.09*** (0.00)
$\Delta\mathbf{LnIPI}$	2.29*** (0.00)	0.01 (0.91)	0.13 (0.72)	0.47*** (0.00)
$\Delta\mathbf{LnNFP}$	0.52*** (0.00)	4.55*** (0.00)	5.20*** (0.00)	6.53*** (0.00)
$\Delta\mathbf{IR}$	0.002 (0.10)	0.001 (0.77)	-0.008 (0.41)	-0.02*** (0.00)
$\Delta\mathbf{K1987}:\mathbf{M09}$	-	-	-	0.15*** (0.00)
$\Delta\mathbf{K1988}:\mathbf{M02}$	-	-	-0.01 (0.58)	-
$\Delta\mathbf{K1988}:\mathbf{M12}$	-	-0.01*** (0.00)	-	-
$\Delta\mathbf{K1989}:\mathbf{M03}$	-0.04*** (0.00)	-	-	-
$\Delta\mathbf{K1991}:\mathbf{M01}$	-	-	-	-0.22*** (0.00)
$\Delta\mathbf{K1993}:\mathbf{M02}$	-	-	-0.001 (0.96)	-
$\Delta\mathbf{K1995}:\mathbf{M05}$	-	-	-	0.04*** (0.00)
$\Delta\mathbf{K1995}:\mathbf{M12}$	-	0.009*** (0.00)	-	-
$\Delta\mathbf{K1996}:\mathbf{M02}$	0.02*** (0.00)	-	-	-
$\Delta\mathbf{K2001}:\mathbf{M02}$	0.01*** (0.00	-	-	-
$\Delta\mathbf{K2001}:\mathbf{M09}$	-	-0.04*** (0.00)	-0.04* (0.07)	-0.12*** (0.00)
$\Delta\mathbf{K2008}:\mathbf{M09}$	0.07*** (0.00)	0.11*** (0.00)	0.10*** (0.00)	0.21*** (0.00)
$\mathbf{ECT_{t-1}}$	-0.01* (0.09)	-0.009* (0.08)	-	-
$\mathbf{R^2}$	0.51	0.21	0.20	0.90
$\mathbf{\bar{R}^2}$	0.46	0.20	0.18	0.89
LRV	0.02	0.03	0.001	0.01
SSR	0.24	0.40	0.40	0.11

Note: LRV is Long-Run Variance and SSR is Sum Squared Resid. The low value of these values provides additional evidence that the analysis results are reliable. The values in the parentheses are probability values. *, ** and *** indicate that coefficients are statistically significant at 10%, 5%, and 1%, respectively.

According to the results shown in Table 6, increases in uncertainty in the stock markets have adversely affected the stock exchange indexes in the short-term. This effect is relatively lower for the NYSE and the SP, and higher for the DJ and the ND when compared to the long-run effect. The general conclusion that can be inferred here is that an increase in uncertainty in stock markets negatively affects the stock indexes in the US both in the short-term and in the long-term.

Increases in the Industrial Production Index had a positive impact on the stock market indexes in the short-term, and the index bearing the highest impact was the NYSE. The short-term effects of the IPI for all stock exchange indexes are found to be lower than its long-term effect.

Increases in the Non-Agricultural Employment have also positively affected stock market indexes in the short-term. As in long-term analysis, the index bearing the highest impact is the Nasdaq100 technology index. Therefore, it is beneficial for investors specially to follow the developments in the Non-Agricultural Employment of the US when engaging in trading in stocks in the Nasdaq100 technology index.

The short-term effect of changes in interest rates on stock exchange indexes is not statistically significant except for the Nasdaq100. Therefore, it will be sufficient for individuals and institutions who trade in the US stock exchanges to consider the FED's interest policies only in their transactions related to Nasdaq100.

In the estimation of the four models, the coefficients of the error correction terms were found to be negative and statistically significant. In this case, it can be concluded that the error correction mechanisms of the models are working and the analyses performed are reliable.

3.8 Causality Test

In this study, the causality effects of uncertainties in stock markets on the stock exchange indexesare analyzed using the LBGC test developed by Li, Balcilar, Gupta, and Chang (2016), since the analysis period is long and the stock market may react differently to events happened in the short-term. In this method, causality relationships in different sub-periods can be examined in more detail.

While testing the existence of a causality relationship from X to Y in this method, the following equation is used as in Granger (1969):

$$Y_t = \phi_0 + \phi_{11}Y_{t-1} + \phi_{12}Y_{t-2} + \cdots + \phi_{1k}Y_{t-k} + \phi_{21}X_{t-1} + \phi_{22}X_{t-2} + \cdots + \phi_{2k}Y_{t-k} + e_t \quad (19)$$

The notations used in Equation (19) are:

k: Optimum lag length

e_t: A series of error terms with White Noise process

Equation (19) can also be written in the form of a matrix, as follows:

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (20)$$

While calculating the test statistics in the LBGC method, a certain number of observations (60 in this study) is obtained, window (sample, sub-analysis period) size is determined and then the test statistics is calculated for this window. Then, the window is moved by removing the first observation from the analysis and including a new observation from the next period. In this way, test statistics for each date can be computed except for the period that leaves the beginning. Because of this systematic, the test is also called "Causality Test in Sliding Windows" or "Rolling Windows Causality Test". In Equation (19), the existence of a causality relationship from X to Y is tested with the hypotheses $\phi_{2k} = 0, k = 1, 2, \ldots p$. The optimal lag length here is p.

H_0: $\phi_{2k} = 0$ There is no causal relationship from X to Y.

H_1: $\phi_{2k} \neq 0$ There is causal relationship from X to Y.

The critical values required to test these hypotheses are obtained with the help of bootstrap.

$$\text{If Calculated Test Statistics} > \text{Critical Value} \quad (21)$$

Then H_0 hypothesis is rejected and a causal relationship is determined between the series.

When both sides of inequality are divided by the Critical Value, then Equation (21) becomes

$$\text{New Test Statistics} > 1 \quad (22)$$

In other words, when the graph is located on the line y = 1, it will be decided that there is a causal relationship. (Chang vd. 2017) as shown in Figure 2. In the LBGC method, the causality relationship between the series can be observed period by period with the help of graphical analysis.

In this study, causality relationships from uncertainty in stock markets to the NYSE are examined with the LBHC causality test[10] and the results are presented in Figure 2.

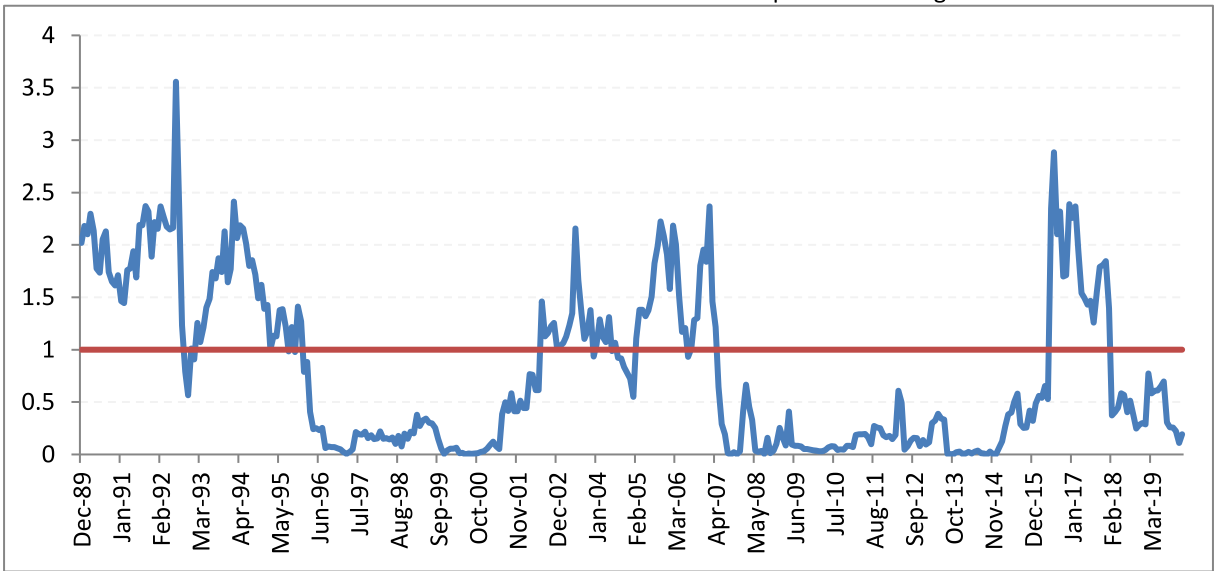

Figure. 2. **Causality Relationship from Uncertainty in Stock Markets to NYSE**

[10] For this test, Gauss 10 program and codes written in this programming language by Li vd. (2016) is used. These codes are received from Veli Yılancı from Sakarya University we thank him for this contribution.

According to Figure 2, causality relations are observed from uncertainty in stock markets to the NYSE for the periods between December 1989 and September 1992, February 1993-December 1995, July 2002-July 2004, February 2005-April 2007 and June 2016-January 2018. When these periods are taken into consideration, it is noticed that there are periods in which the FED changed its monetary policies. Causality relationships from uncertainty in stock markets to the S&P500 are examined with the LBHC causality test and the results are presented in Figure 3.

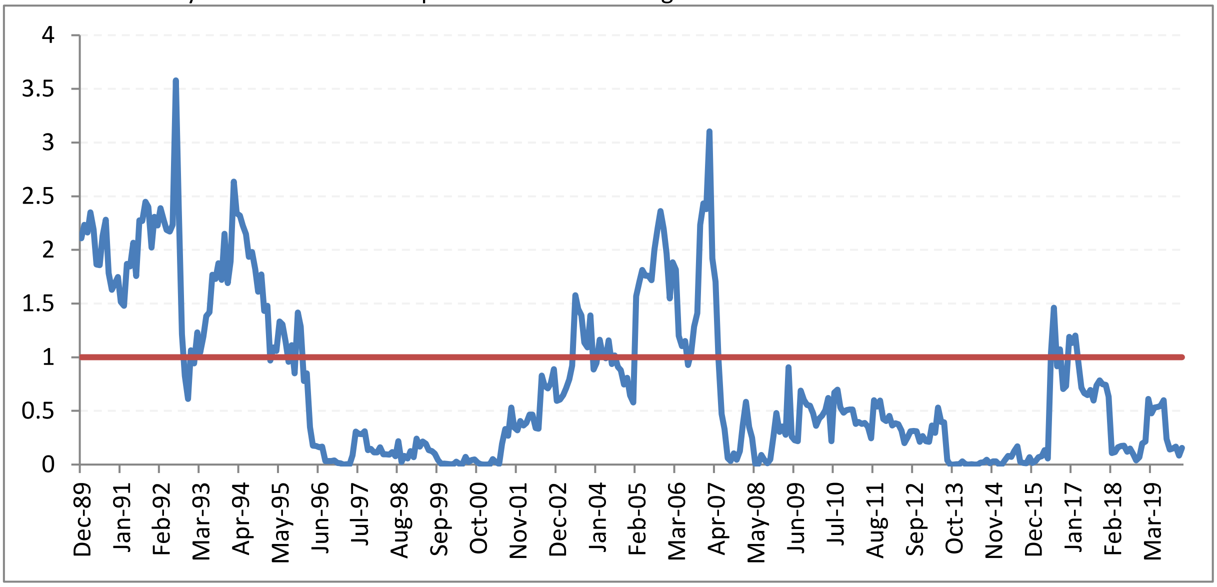

Figure. 3. **Causality Relations from Uncertainty in Stock Markets to S&P 500**

According to Figure 3, causality relationships exist from uncertainty in stock markets to the S&P500 for the periods between December 1989-December 1995, June 2003-July 2004, February 2005-April 2007 and June 2016-February 2017. It is noteworthy that these periods are the periods when the FED changed its monetary policies. The causality relationships from the uncertainty in the stock markets towards the Dow Jones are examined with the LBHC causality test and the results are presented in Figure 4.

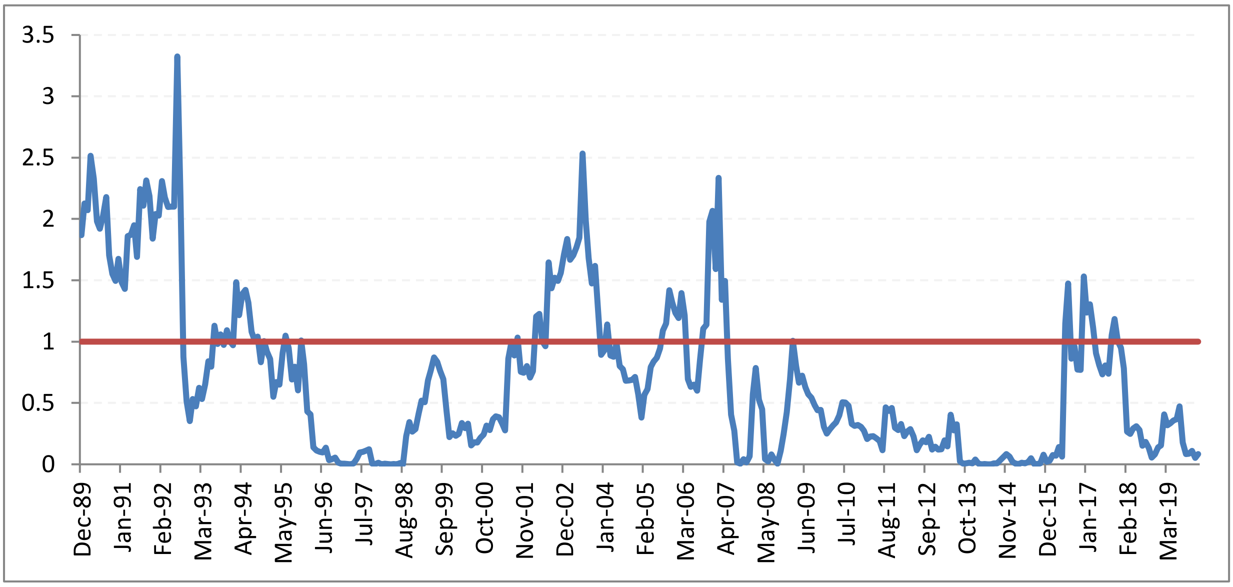

Figure. 4. Causality Relations from Uncertainty in Stock Markets to Dow Jones

According to Figure 4, there exist causality relationships from uncertainty in stock markets to the Dow Jones index for the periods between December 1989-August 1992, July 1993-November 1994, March 2002-February 2004, August 2005-March 2006, September 2006-April 2007 and June

2016-November 2017. Among these periods, the noteworthy ones are: 1990-1991 is period when the First Gulf War broke out, 2002-2004 period is when the FED's interest rates decreased from 5% to 0% and also corresponds to the beginning of the II. Gulf War in March 2003 and the 2016-2018 is the period when the FED gradually increased its interest rates. The causality relationships from the uncertainty in the stock markets to the Nasdaq100 index are examined with the LBHC causality test and the results are presented in Figure 5.

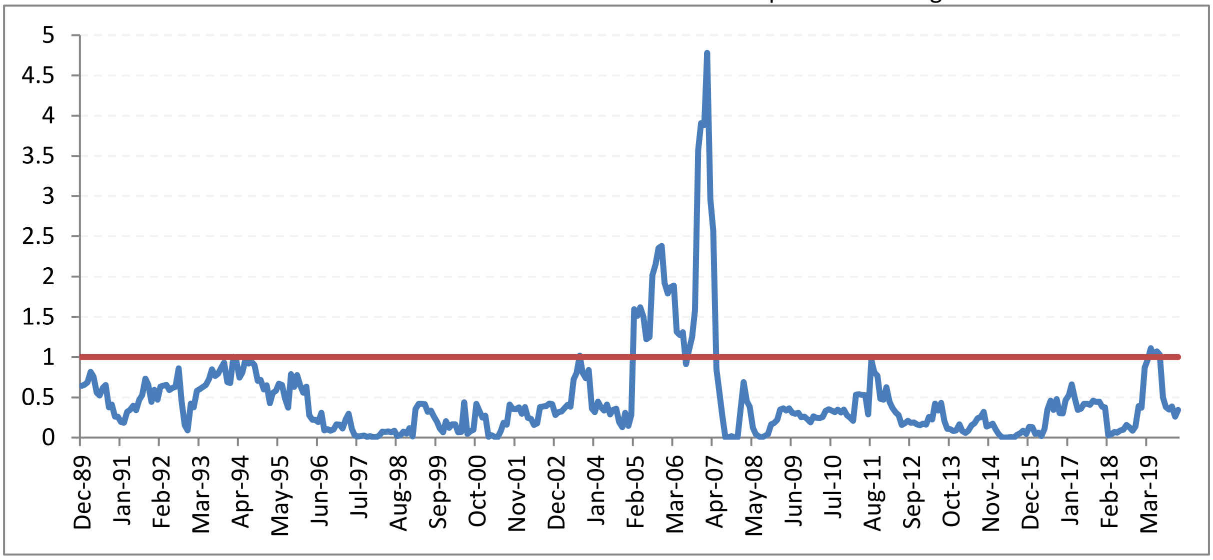

Figure. 5. **Causality Relations from Uncertainty in Stock Markets to Nasdaq100**

According to Figure 5, a causal relationship from the uncertainty in stock markets to the Nasdaq100 index is observed only in the period before the 2008 global economic crisis and in a short period between April 2019 and July 2019. This finding is important in terms of showing that technology shares are not affected by the uncertainties in stock markets.

4. Conclusion

In this study, the effects of the uncertainity on investors' reaction is measured. For this purpose, the relationship between US Equity Market Uncertainty Index (EMUI) and returns of the NYSE, the S&P 500, the Dow Jones and the Nasdaq100 indexes traded in the US are analyzed by using monthly data spanning through 1985:M01-2020:M01. In addition, control variables of the US Industrial Production Index, the Non-Agricultural Employment data, and the FED interest rate are included in the analysis as indicators of real economic activities and monetary policies. The present study, four different econometric models have been evaluated.

The stationarity of the series is investigated by Carrion-i-Silvestre et al. (2009) multiple structural break unit root test and it has been determined that all series are stationary at the first difference but not at their level values. The existence of cointegration between the series is tested by Maki (2012) multiple structural break cointegration test and it is found that the series in the models are cointegrated, that is, they move in line with each other in the long-term. Based on this finding, it can be inferred that the stock markets in the US are affected by the uncertainties in this market, real factors such as Industrial Production and Non-Agricultural Employment, and the Fed's interest rate decisions.

Long and short-term analyses between the series are performed with the Dynamic OLS method. According to the results of the long-term analysis, increases in uncertainty in the stock markets have adversely affected all four exchanges, and the index that received the greatest impact is the NYSE. The increase in Industrial Production Index has positively affected all four stock exchange indexes, and the stock exchange bearing the greatest impact is the NYSE. The Non-Agricultural Employment growth has also positively affected all exchange indexes with Nasdaq100 being the most affected index. Moreover, increases in interest rate have negatively affected all four stock market indexes operating in the US. This shows that time deposits are substitutes for investing in stock exchanges in the eyes of the investors. What is interesting here is that the index that was most affected by the changes in the interest rate policies implemented by the FED is the Nasdaq100 technology index. Subsequently, results obtained from the present study is consistent with the findings of Arouri et al. (2016).

According to the results of the short-term analysis, increases in uncertainty in the stock markets have adversely affected the stock exchange indexes in the short-term. This effect is relatively lower for the NYSE and the SP, and higher for the DJ and the ND. The general conclusion that can be drawn here is that an increase in uncertainty in stock markets negatively affects stock exchange indexes operating in the US both in the short-run and in the long-run. Increases in the Industrial Production Index had a positive impact on the stock market indexes in the short-term, and the index bearing the highest impact was the NYSE. The short-run effects of the Industrial Production Index for all stock exchange indexes are lower than those in the long-run. Increases in the Non-Agricultural Employment have also positively affected stock market indexes in the short-term. As in long-term analysis, the index bearing the highest impact is the Nasdaq100 technology index. Therefore, it is beneficial for investors specially to follow the developments in the Non-Agricultural Employment of the US when engaging in trading in stocks in the Nasdaq100 technology index. The short-term effect of changes in interest rates on stock exchange indexes is not statistically significant except for the Nasdaq100. Therefore, it will be sufficient for individuals and institutions who trade in the US stock exchanges to consider the FED's interest policies only in their transactions related to Nasdaq100. In the estimation of the four models, the coefficients of the error correction terms were found to be negative and statistically significant. Based on this finding, it can be claimed that error correction mechanisms of the models worked well, thus, the conducted analyses are reliable.

The effects of uncertainties in stock markets on four stock market indexes operating in the US are analyzed using the time-varying causality test developed by Li, Balcilar, Gupta and Chang (2016). According to the test results, uncertainties in stock markets possess causality effects on the NYSE, the S&P500 and the Dow Jones, but this effect is relatively smaller on the Nasdaq100. Therefore, it can be stated that technology shares are less affected by the level of uncertainty in stock markets. In general, it is observed that the periods in which uncertainties in the stock markets had an increased effect on the stock exchange indexes correspond to periods the Federal Reserve has played a more active role in the monetary policy of the US. The results obtained at this stage of the study are also in line with the findings of Ongan and Gocer (2017).

The findings obtained from the present study suggest that the four stock exchanges at hand are being significantly affected by the uncertainties arising in the US economy. In order to subdue this negative effect, press organizations should be very sensitive when selecting the content of their news and avoid speculative journalism. Also, individual and institutional agents who steer economic policies should increase efforts to reduce possible uncertainties in the markets. Individuals and institutions should deliberately monitor Uncertainty Index in Stock Markets, the US Industrial Production Index and the Non-Agricultural Employment data when investing in the NYSE, should closely follow the US Non-Agricultural Employment data for trading in the S&P500 and the Dow Jones, and should not forget to take into account the US Industrial Production Index, the Non-Agricultural Employment and FED's monetary policies for engaging in transactions in Nasdaq100.

References

[1] Arouri, M., Estay, C., Rault, C. and Roubaud, D. (2016), “Economic Policy Uncertainty and Stock Markets: Long-Run Evidence from the US.” Finance Research Letters, 18, 136-141.

[2] Baker, S. R., Bloom, N. and Davis, S. J. (2016), “Measuring Economic Policy Uncertainty.” Quarterly Journal of Economics, 131(4), 1593-1636.

[3] Baker, S. R., Bloom, N. and Davis, S. J. (2020), “US Equity Market Uncertainty Index.” https://www.policyuncertainty.com/equity_uncert.html, (Accessed: 21.02.2020).

[4] Bilir, H. (2018), “Ocak Ayı Etkisinin Türk Sermaye Piyasalarında Farklı BIST Endekslerine Göre Analizi.” Sosyokeonomi, 26(36), 145 – 160.

[5] Bloomberght (2016), 4 Soruda 1987 Borsa Krizi. <https://businessht.bloomberght.com/piyasalar/haber/1312483-4-soruda-1987-borsa-krizi>, 21.02.2020.

[6] Carrion-i-Silvestre, J. L. and Sanso, A. (2006), “Testing the Null of Cointegration with Structural Breaks.” Oxford Bulletin of Economics and Statistics, 68(5), 623 - 646.

[7] Carrion-i-Silvestre, J. L., Kim, D and Perron, P. (2009), “GLS-Based Unit Root Tests with Multiple Structural Breaks Under Both the Null and the Alternative Hypotheses.” Econometric Theory, 25, 1754 - 1792.

[8] Chang, T., Tsai, S. L. and Haga, K. A. (2017), “Uncovering the Interrelationship between the U.S. Stock and Housing Markets: A Bootstrap Rolling Window Granger Causality Approach.”

Applied Economics, 49(58), 5841-5848.
[9] Diamond, P. and Vartiainen, H. (2016), Behavioral Economics and Its Applications. (Çev: Kamilçelebi, H.). Nobel Yayınevi, İstanbul.
[10] DW (2011), ABD Ekonomisi İpten Döndü, <https://www.dw.com/tr/abd-ekonomisi-ipten-d%C3%B6nd%C3%BC/a-15287086>, 22.02.2020.
[11] Engle, R. F. and Granger, C. W. J. (1987), "Cointegration and Error-Correction: Representation, Estimation and Testing." Econometrica, 66, 251 - 276.
[12] Feve, P. (2015), The Lucas Critique. Toulouse School of Economics, GREMAQ, IDEI and IUF, MF 508.
[13] Finans Webde (2019), S&P 500 Endeksi Nedir? <https://finanswebde.com/s-p-500-endeksi-nedir/b/5d97359b7f8c7e0038d65cc1>, 22.02.2020.
[14] FRBP (2020), Federal Reserve Bank of Philadelphia, Historical Data Files for the Real-Time Data Set, Nonfarm Payroll Employment (EMPLOY), <https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/data-files/employ>,15.02.2020.
[15] Gábor-Tóth, E. and Georgarakos, D. (2017), Economic Policy Uncertainty and Stock Market Participation.https://www.ecb.europa.eu/pub/conferences/shared/pdf/20171214_5th_conferen
ce_hfcs/Session2_HFCNShorter_Georgarakos_Paper.pdf, (Accessed: 21.02.2020).
[16] Gao, J., Zhu, S., O'Sullivan, N. and Sherman, M. (2019), "The Role of Economic Uncertainty in UK Stock Returns." Journal of Risk and Financial Management, 12(5), 1 – 16.
[17] GCM (2020), NASDAQ 100. https://www.gcmforex.com/yatirim-araclari/borsa-endeksleri/nasdaq-100/, (Accessed: 22.02.2020).
[18] Gilal, A. M. (2019), Economic Policy Uncertainty and Stock Market Returns in Indonesia. DOI: 10.13140/RG.2.2.10905.88168, 1-16.
[19] Granger, C. W. J. and Newbold, P. (1974), "Spurious Regressions in Econometrics." Journal of Econometrics, 2(2), 111 – 120.
[20] Greene, W. (2002), Econometric Analysis. (Fifth Edition). New York University, Prentice Hall, New Jersey.
[21] Gregory, A. W. and Hansen, B. E. (1996), "Residual-Based Tests for Cointegration in Models with Regime Shifts." Journal of Econometrics, 70(1), 99 - 126.
[22] Guerrien, B. (1999), Neo-Klasik İktisat. İletişim Yayınları, İstanbul.
[23] İkon Menkul (2020), Borsa Endeksleri., <https://ikonmenkul.com.tr/sp500-endeksi>, 22.02.2020.
[24] Johansen, S. (1988), "Statistical Analysis of Cointegration Vectors." Journal of Economics Dynamic and Control, 12(2 - 3), 231 – 254.
[25] Kahneman, D. and Tversky, A. (1979), "Prospect Theory: An Analysis of Decision under Risk." Econometrica 47(2), 263 - 291.
[26] Kang, K. (2014), What are Unit Roots in Statistics, and What are Their Significance? What is the Effect of a Unit Root on The First Difference? https://www.quora.com/What-are-unit-roots-in-statistics-and-what-are-their-significance-What-is-the-effect-of-a-unit-root-on-the-first-difference, (Accessed: 28.04.2020).
[27] Kapetanios, G. (2005), "Unit-Root Testing against the Alternative Hypothesis of up to m Structural Breaks." Journal of Time Series Analysis, 26(1), 123–133.
[28] Lam, S.-S. and Zhang, W. (2014), "Does Policy Uncertainty Matter for International Equity Markets?" ACSEP Basic Research Working Paper, No. 3.
[29] Li, X., Balcilar, M., Gupta, M. and Chang, T. (2016), "The Causal Relationship between Economic Policy Uncertainty and Stock Returns in China and India: Evidence from A Bootstrap Rolling-Window Approach." Emerging Markets Finance and Trade, 52(3), 674–689.
[30] Lucas, R. E. (1976), "Econometric Policy Evaluation: A Critique." Carnegie-Rochester Conference Series on Public Policy, 1, 19 – 46.
[31] Lütkepohl, H. and Kratzig, M. (2004), Applied Time Series Econometrics. Cambridge University Press, New York.
[32] Macrotrends (2020), Federal Funds Rate - 62 Year Historical Chart, <https://www.macrotrends.net/2015/fed-funds-rate-historical-chart>, 15.02.2020.
[33] Maki, D. (2012), "Tests for Cointegration Allowing for an Unknown Number of Breaks." Economic Modelling, 29(5), 2011 - 2015.
[34] Muth, J. F. (1961), "Rational Expectations and the Theory of Price Movements." Econometrica, 29(3), 315-335.
[35] Nobel Prize (2002), The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2002, <https://www.nobelprize.org/prizes/economic-sciences/2002/summary/>, 20.02.2020.
[36] OECD (2020), Organization of Economic Cooperation and Development. Industrial Production., <https://countryeconomy.com/business/indust

rial-production/usa>, 17.02.2020.

[37] Ongan, S. and Gocer, I. (2017), “Testing the Causalities between Economic Policy Uncertainty and the US Stock Indices: Applications of Linear and Nonlinear Approaches.” Annals of Financial Economics, 12(4), 1 – 20.

[38] Sargent, T. J. and Wallace, N. (1975), "Rational" Expectations, the Optimal Monetary Instrument, and the Optimal Money Supply Rule. Journal of Political Economy, 83(2), 241-254

[39] Schettkat, R. (2018), “The Behavioral Economics of John Maynard Keynes.” Schumpeter Discussion Papers, No. 2018-007.

[40] Smith, A. (1759), Ahlaki Duygular Kuramı. (Çev: Berkay Tartıcı). Liber plus Yayınları, İstanbul.

[41] Stock, J. and Watson, M. W. (1993), “A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems.” Econometrica, 61(4), 783 - 820.

[42] Tradingview (2020), Dow Jones Endüstri Ortalaması Endeksi. <https://tr.tradingview.com/symbols/DJ-DJI/>, 22.02.2020.

[43] Westerlund, J. and Edgerton, D. (2006), “Simple Tests for Cointegration in Dependent Panels with Structural Breaks.” Lund University, Department of Economics, Working Papers, No. 13.

[44] Yahoo (2020), NYSE - NYSE Delayed Price. Currency in USD. <https://finance.yahoo.com/quote/%5ENYA/history?period1=126316800&period2=1581984000&interval=1d&filter=history&frequency=1d>, 17.02.2020.