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CAUSAL FACTORS BEHIND FINANCIAL MARKET FLUCTUATIONS DURING GLOBAL HEALTH CRISES

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Abstract

This study investigates the causes of fluctuations in the financial markets during the COVID-19 pandemic period as a global health crisis. While gold, oil, and stocks prices were used to represent financial markets in the study, new cases, new deaths, and total case numbers were used to evaluate the effects of COVID-19. EPU, EMVI, VIX, and IDEMV indices are used for market uncertainties. The research period consists of the daily data set between January 22, 2020, and March 16, 2022. The NARDL model was used as a research model. According to the research results, while gold prices are affected by the COVID-19 pandemic variables in any case, oil prices only respond to positive changes. Uncertainty in financial markets affects stock and oil prices negatively, while it affects gold prices positively.

Keywords: COVID-19 pandemic, Gold Prices, Oil Prices, Stock Prices, Fluctuation in The Market.

JEL Classification: C58, G10, G14, G15.

KÜRESEL SAĞLIK KRİZLERİ DÖNEMİNDE FİNANSAL PİYASALARDAKİ DALGALANMALARIN NEDENLERİ

Öz

Bu çalışma, küresel bir sağlık krizi olan COVID-19 pandemisi döneminde finansal piyasalarda yaşanan dalgalanmaların nedenlerini araştırmayı amaçlamaktadır. Çalışmada finansal piyasaları temsil etmek için altın, petrol ve hisse senetleri fiyatları kullanılırken, COVID-19 'un etkilerini değerlendirmek için yeni vakalar, yeni ölümler ve toplam vaka sayıları kullanılmıştır. Piyasa belirsizlikleri için EPU, EMVI, VIX ve IDEMV endeksleri kullanılmıştır. Araştırma dönemi 22 Ocak 2020 – 16 Mart 2022 tarihleri arasındaki günlük veri setinden oluşmaktadır. Araştırma modeli olarak NARDL modeli kullanılmıştır. Araştırma sonuçlarına göre altın fiyatları her durumda COVID-19 salgını değişkenlerinden etkilenirken, petrol fiyatları bu değişkenlerin yalnızca pozitif değişimlerine tepki vermektedir. Finansal piyasalardaki belirsizlik altın fiyatlarını ise pozitif yönde etkilerken; hisse senedi ve petrol fiyatlarını ise negatif yönde etkilemektedir.

Anahtar Kelimeler: COVID-19 Salgını, Altın Fiyatları, Petrol Fiyatları, Hisse Senedi Fiyatları, Piyasadaki Fiyat Dalgalanmaları.

JEL Sınıflaması: C58, G10, G14, G15

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1. Introduction

The COVID-19 pandemic, which emerged in Wuhan, China, in December 2019, led to new risk factors occurring for the uncertainty in financial markets with many factors such as the number of cases and deaths due to COVID-19 pandemic, vaccination rates, lockdown decisions by states, travel restrictions and remote working in offices (Tuna & Tuna, 2022). This pandemic caused an increase in economic uncertainty, influenced many sectors at different levels, and led to fluctuations in global financial markets (Zeinedini et al., 2022). Consequently, 143 countries in 2020 experienced negative economic growth, with a worldwide average of −3.59% (World Bank, 2021).

Although the COVID-19 pandemic caused diversification of investment tools in the portfolios, it did not adversely affect the interest in traditional investment tools such as stocks, oil, and gold. However, with the COVID-19 pandemic, the correlations among investment tools varied, affecting the distribution of portfolio allocations. In many studies, it is stated that there is a strong positive correlation between oil and gold prices in the long term (Shahzad et al., 2019; Šimáková, 2011; Singh et al., 2019; Tanin et al., 2022), but this correlation is at deficient levels during periods of uncertainty and volatility (Tanin et al., 2022). In the long run, gold prices and stock market returns indicate a balanced relationship (Al-Ameer et al., 2018; Gokmenoglu & Fazlollahi, 2015). The decrease in travel as a result of the measures due to the COVID-19 pandemic and the fact that Saudi Arabia did not comply with the quotas and increased oil production on March 9, 2020, caused the oil prices to fall from $ 100 at the beginning of 2020 to $ 20 at the end of April 2020 (Duran & Acar, 2020; Sharif et al., 2020). Although there is a negative and significant correlation between oil and the stock market in normal market conditions (Cunado & de Gracia, 2014; Filis et al., 2011), this correlation lost its effect during the Covid-19 Pandemic period, and the stock market experienced one of the biggest collapses in its history and lost in value by 26 % in four days in March 2020 (Mazur et al., 2021). The increasing uncertainty and the decrease in oil and stock market prices caused investors to turn to gold to hedge against global risks (Salisu et al., 2021). Therefore, gold prices reached a record high in August 2020. As a result of these events, there is a moderate positive correlation between oil and the stock market, which showed a falling tendency both before COVID-19 and during the first spread period of COVID-19 (July 2018 – April 2020).

In contrast, there is a negative correlation between the stock market and gold for the same period (Mensi et al., 2022). The Covid-19 Pandemic adversely affects the stock market (Wang & Liu, 2022). In the third quarter of 2020, the COVID-19 pandemic also affected gold prices, and instead of the traditional increase in gold returns seen in the fall, gold prices decreased (Bentes et al., 2022). These results in the literature favor the conclusion that the correlation among investment tools varied in fluctuation periods; thus, portfolio options were also affected. However, the question "***What are the factors that cause fluctuations in financial markets during the COVID-19 pandemic period, which is a global epidemic that is controlled and slowed down in some periods****?*" comes up at this point. This study seeks to answer this question because many sources of risk and uncertainty that financial markets do not expect came to the fore with the COVID-19 pandemic.

Following this goal, while using stock, oil, and gold prices to represent financial markets for economic uncertainty, EPU (economic policy uncertainty), for the uncertainty in the securities market, EMVI (Index of Equity Market Uncertainty), to see if the fear of uncertainty affects financial tools, VIX (Volatility Index), which is an index used for measuring the degree of the fear, because of allowing to understand better the effect of uncertainty and epidemic panic on economic tools (Yi et al., 2021), IDEMV (Infectious Disease Equity Market Volatility) are preferred in criteria used for fluctuations in the market. The number of new cases per day, daily deaths due to Covid-19, and total deaths were used as the variables related to Covid-19.

This study will contribute to the literature on several essential points. The first contribution pertains to the research question, "What factors cause fluctuations in financial markets in the Covid-19 Pandemic?". In the study, first of all, the preferred data set is critical while determining the source of the changes in the financial markets during the COVID-19 period. EPU, EMVI, IDEMV, and VIX, which are variables that consider both the uncertainties in the general economic situation and the uncertainties arising due to COVID-19, as well as the investor sentiment, were used together for uncertainty. VIX is a crucial index for financial markets. VIX is related to macroeconomic conditions, but it cannot give information changes through social media and investor sentiment (Dutta et al., 2021; Mo et al., 2019). News from the media also affects financial markets by increasing investor sentiment (Bollen et al., 2011). Baker et al. (2019) proposed a newspaper-based volatility measure called the equity market volatility index (EMVI) to fill this gap. According to Alqahtani et al. (2020), EMVI is superior to the VIX in terms of the predictability of stock markets. Therefore, it is essential to include EMVI and VIX indices separately in the study. In addition, the IDEMV index, created based on news, was used to evaluate the volatility in the market due to the pandemic, and the EPU index was used for general economic uncertainty. EPU is an essential factor that affects stock prices (Brogaard & Detzel, 2015; Christou et al., 2017; Dakhlaoui & Aloui, 2016; Damianov & Elsayed, 2018; Das & Kumar, 2018; Dieci et al., 2018; Guo et al., 2018; Kannadhasan & Das, 2020; Ko & Lee, 2015; Phan et al., 2018). According to some studies in the literature, EPU causes an increase in stock prices (Antonakakis et al., 2013; Kang & Ratti, 2014). However, some studies indicate that increased EPU decreases stock returns (Arouri et al., 2016; Chiang, 2021; Christou et al., 2017). According to Kannadhasan et al. (2020), the dependence of stock returns on the EPU is asymmetrical. Therefore, using all selected uncertainty indices together is essential in terms of the obtained results. New case numbers, new death numbers, and total case numbers are used for the COVID-19 pandemic. Stock, oil, and gold are used as investment tools. Oil and gold are the assets used actively in portfolio risk management (Adekoya et al., 2021; Benlagha & El Omari, 2022; Gharib et al., 2021; X. Li et al., 2021; Wei et al., 2022). Stock is preferred because it is an investment tool with high trading volume in financial markets. In addition, stock prices are directly and indirectly affected because oil is used in production processes as an energy source or raw material. Gold affects stock investments as an essential hedging tool in all periods (Tuna, 2022). Therefore, all analyses must be made separately for stocks, oil, and gold to generalize the results obtained in financial markets.

The second significant contribution pertains to the method used. The model used is significant in examining the effects of positive and negative changes in factors such as the number of new cases and deaths resulting from the COVID-19 pandemic, which has affected the world's financial markets. The nonlinear ARDL model, in which the effect of negative and positive changes in the numbers of new cases and deaths can be separately evaluated, is crucial for examining the long-term correlations.

Another significant contribution is that the changes in gold, oil, and stock prices, which constitute an essential part of financial markets, are examined together. Therefore, the findings obtained from the study will contribute to the new information needed by academicians and practitioners by enabling inter-market comparisons. In the current literature, the necessary evaluations for a single investment tool are made with either COVID-19 pandemic-related variables or limited variables for some selected macroeconomic indicators. However, all analyses were made with this study's extensive data set.

This study consists of five parts. After the introduction, the literature review is included; in the third part, the data set and method used; in the fourth part, the empirical findings obtained; and in the final part, the evaluations are included.

2. Literature Review

Great pandemics that affected financial markets in the recent past are SARS and Covid-19. It is stated in the literature that SARS affected economies locally; however, Covid-19 affected all markets globally (Loh, 2006; Nippani & Washer, 2004). In addition, this effect among financial markets weakens over time and loses its effect (Chen et al., 2018). Most studies on the COVID-19 pandemic also support the conclusion that the impact of the pandemic is global. Besides different uncertainty indices, which are essential determiners of risk, the effect of Covid-19-related factors on financial markets was examined in this study because the COVID-19 pandemic affects the financial markets and the prices of investment tools in different ways. Because the COVID-19 disease is contagious, it progresses severely, and the death rate is much higher than in other influenza cases, the measures taken regarding social and economic life caused adverse effects on financial markets (Çevik et al., 2020; Estrada et al., 2020). Thus, this resulted in a significant increase in the volatility in financial markets.

Investors commonly prefer investment tools such as oil, gold, and stock for hedging and diversification. Factors affecting the risk component, one of the critical decision criteria in portfolio preferences, can be affected by different factors. For example, although interest, exchange rate, and inflation are considered essential risk components, the COVID-19 pandemic also caused factors such as the number of new cases and deaths to emerge in the financial markets. Therefore, COVID-19-related factors lead to new systematic risk elements in financial markets (Zhang et al., 2020). When the stock market, gold, and oil transactions are compared before and after January 2020, when the first case was identified in the USA, it is seen that a sudden change occurred in the market with the pandemic; volatility clusters increased and changed significantly compared to the pre-pandemic period (Mensi et al., 2022; Mzoughi et al., 2020). In the period January 22, 2020, to April 17, 2020, when the first COVID-19 cases began to appear, it was observed in the study of stock market returns conducted in 64 countries that stock market returns were inversely proportional to the number of cases and responded less to the number of deaths (Ashraf, 2020). It is seen in the literature that different indicators used for the COVID-19 pandemic in other markets give different results (Y. Li et al., 2020; Liao et al., 2021; Zeinedini et al., 2022). For example, IDEMV, which is accepted as an infectious disease monitor and rises with the disease, is more robust than VIX (Li et al., 2020). While the EPU, widely used for market uncertainty, has a significant and positive effect on the US stock market volatility, the reported new case and death numbers have a significant and negative impact on stock indices volatility (Chowdhury et al., 2022). The number of deaths and Covid 19 panic negatively affect crude oil; the number of deaths positively affects gold, and the number of new infections affects gold and oil differently during different periods (Atri et al., 2021).

This COVID-19-oriented effect is widely studied using different variables such as death and case numbers, IDEMV, VIX, and EPU. According to the results of the study, there is a long-term correlation between Covid-19, EPU, and volatility (Chowdhury et al., 2022). Uncertainties in the market during the Covid-19 period become more evident by increasing and appearing more clearly in the long term (Hong et al., 2022). The IDEMV index, which is used to evaluate the effect of the uncertainties due to COVID-19 in financial markets, also acts in the same direction as the EPU and supports this result (Rubbaniy et al., 2023).

According to the literature, there is a long-term permanent effect between the number of COVID-19 cases and stock, gold, and oil prices (Tuna & Tuna, 2022). Therefore, economic uncertainties during the COVID-19 period have more noticeable effects on oil prices (Khalfaoui et al., 2022). Even the impact on oil prices is stronger than the gold market (Wei et al., 2022). Developed stock markets are more affected by the COVID-19 pandemic than the other periods (Dong et al., 2021). The number of cases and deaths related to COVID-19 shows its effect by affecting stock market returns and oil prices negatively (Al-Awadhi et al., 2020; Ashraf, 2020; Atri et al., 2021), and gold prices positively (Atri et al., 2021; S. Li et al., 2022). While stock prices have a significant negative correlation with oil, they have no significant correlation with gold in the COVID-19 period (Zeinedini et al., 2022).

The effects of the factors related to the COVID-19 pandemic on gold, stock, and oil prices for different markets or the effect of uncertainty indices such as EPU, VIX, and IDEMV on financial markets are examined in the literature. However, the absence of any study examining the asymmetric effects of COVID-19-related factors and uncertainties such as EPU, EMVI, VIX, and IDEMV created for different purposes on gold, oil, and stock markets distinguishes this study from the literature. For that reason, this study will contribute to the literature.

3. Data Set and Methodology

3.1. Methodology

The purpose of this study is to examine the effect of the variables for the risk and uncertainties on financial markets and the asymmetric effect of the COVID-19 pandemic using the NARDL (Nonlinear Autoregressive Distributed Lag) model. The NARDL approach, proposed by Shin, Yu, and Greenwood-Nimmo (2014), has various advantages over the conventional ARDL model. First, it is no linearity assumption. Second, the NARDL model checks for the asymmetric impact of positive and negative influences in the long run. Third, the NARDL model also captures cointegration for a single equation (Çıtak et al., 2020).

To investigate the long-run relationship between ınvestment tools (gold, oil and stock prices), new case, new death, total case, EPU, IDEMV, EMVI, VIX, the following linear equation framework can be modelled:

$$StockExchange_t=\beta_0+\beta_1 EPU_t+\beta_2 IDEMV_t+\beta_3 EMVI_t + \beta_4 VIX_t + \beta_5 totalcase_t + \beta_6 newcase_t+\beta_7 newdeath_t+ \varepsilon t \quad (1a)$$

$$Oil t=\beta_0+\beta_1 EPU_t+\beta_2 IDEMV_t+ \beta_3 EMVI_t + \beta_4 VIX_t + \beta_5 totalcase_t + \beta_6 newcase_t + \beta_7 newdeath_t+ \varepsilon t \quad (1b)$$

$$Gold t=\beta_0+\beta_1 EPU_t+\beta_2 IDEMV_t+ \beta_3 EMVI_t + \beta_4 VIX_t + \beta_5 totalcase_t + \beta_6 newcase_t+ \beta_7 newdeath_t+ \varepsilon t \quad (1c)$$

Where newcase, newdeath, totalcase, EPU, *IDEMV*, *EMVI*, *VIX* represent newcase, newdeath, totalcase in Covid-19 period, economic policy uncertainty policy ındex, Infectious Disease Equity Market Volatility, Index of Equity Market Uncertainty, Volatility Index in given time period t, respectively. β_i represents the long-run coefficients, and ε_t is an error term.

Eq. (2a, 2b, 2c) to express the asymmetric long-run regression of gold, oil and stock price as follows:

$$Stock t= \delta_0+ \delta_1 EPU_t+ \delta_2 IDEMV_t+ \delta_3 EMVI_t + \delta_4 VIX_t + \delta_5 totalcase_t + \delta_6 (newcase^+_t)+ \delta_7 (newcase^-_t)+ \delta_8 (newdeath^+_t)+ \delta_9 (newdeath^-_t + \varepsilon t \quad (2a)$$

$$Oil t= \delta_0+ \delta_1 EPU_t+ \delta_2 IDEMV_t+ \delta_3 EMVI_t + \delta_4 VIX_t + \delta_5 totalcase_t + \delta_6 (newcase^+_t)+ \delta_7 (newcase^-_t)+ \delta_8 (newdeath^+_t)+ \delta_9 (newdeath^-_t + \varepsilon t \quad (2b)$$

$$\text{Goldt}= \delta_0+ \delta_1\text{EPU}_t+ \delta_2 IDEMV_t+ \delta_3 EMVI_t + \delta_4 VIX_t + \delta_5\text{totalcase}_t + \delta_6(\text{newcase}^+_t)+ \delta_7(\text{newcase}^-_t)+ \delta_8(\text{newdeath}^+_t)+ \delta_9(\text{newdeath}^-_t + \varepsilon t \quad (2c)$$

Where δ_i indicate coefficients vector for long-run parameters to be estimated and newcase+t, newcase-t, newdeath+t, newdeath-t, totalcase+t, totalcase-t denote the positive and negative partial sum process variation in newcase, newdeath and totalcase, respectively.

Following Shin, Yu, and Greenwood-Nimmo (2014), the values of newcase+t, newcase-t, newdeath+t, newdeath-t, totalcase+t, totalcase-t, can be framed through the equations below (3a, 3b, 3c, and 3d):

$$\text{newcase}+=\sum ti=1\Delta\text{newcase}+i=\sum ti=1\max(\Delta\text{newcase}i,0) \quad (3a)$$

$$\text{newcase}-=\sum ti=1\Delta\text{newcase}-i=\sum ti=1\min(\Delta\text{newcase}i,0) \quad (3b)$$

$$\text{newdeath}+=\sum ti=1\Delta\text{newdeath}+i=\sum ti=1\max(\Delta\text{newdeath}i,0) \quad (3c)$$

$$\text{newdeath}-=\sum ti=1\Delta\text{newdeath}-i=\sum ti=1\min(\Delta\text{newdeath}i,0) \quad (3d)$$

NARDL can be formulated as follows (4a, 4b, and 4c):

$$\Delta\text{stock}_t=\vartheta_0+\sum\vartheta_1\Delta\text{stock}_{t-1}+\sum\vartheta_2\Delta\text{EPU}_{t-1}+\sum\vartheta_3\Delta\text{IDEMV}_{t-1}+\sum\vartheta_4\Delta\text{EMVI}_{t-1}+\sum\vartheta_5\Delta\text{VIX}_{t-1} +\sum\vartheta_6\Delta\text{totalcase}_{t-1}+\sum\vartheta_7\Delta\text{newcase}^+_{t-1}+\sum\vartheta_8\Delta\text{newcase}^-_{t-1}+ \vartheta_9\Delta\text{newdeath}^+_{t-1} +\sum\vartheta_{10}\Delta\text{newdeath}_{t-1} +\zeta_1\text{stock}_{t-1}+ \zeta_2\text{EPU}_{t-1}+ \zeta_3\text{IDEMV}_{t-1}+ \zeta_4\text{EMVI}_{t-1}+ \zeta_5\text{VIX}_{t-1}+ \zeta_6\text{totalcase}_{t-1}+ \zeta_7\text{newcase}^+_{t-1}+ \zeta_8\text{newcase}^-_{t-1}+\zeta_9\text{newdeath}^+_{t-1}+ \zeta_{10}\text{newdeath}^-_{t-1} + \varepsilon t \quad \textit{(4a)}$$

$$\Delta\text{oil}_t=\vartheta_0+\sum\vartheta_1\Delta\text{oil}_{t-1}+\sum\vartheta_2\Delta\text{EPU}_{t-1}+\sum\vartheta_3\Delta\text{IDEMV}_{t-1}+\sum\vartheta_4\Delta\text{EMVI}_{t-1}+\sum\vartheta_5\Delta\text{VIX}_{t-1}+ \sum\vartheta_6\Delta\text{totalcase}_{t-1}+\sum\vartheta_7\Delta\text{newcase}^+_{t-1}+\sum\vartheta_8\Delta\text{newcase}^-_{t-1}+\sum\vartheta_9\Delta\text{newdeath}^+_{t-1} +\sum\vartheta_{10}\Delta\text{newdeath}_{t-1} +\zeta_1\text{oil}_{t-1}+ \zeta_2\text{EPU}_{t-1}+ \zeta_3\text{IDEMV}_{t-1}+ \zeta_4\text{EMVI}_{t-1}+ \zeta_5\text{VIX}_{t-1}+ \zeta_6\text{totalcase}_{t-1}+ \zeta_7\text{newcase}^+_{t-1}+ \zeta_8\text{newcase}^-_{t-1}+ \zeta_9\text{newdeath}^+_{t-1}+ \zeta_{10}\text{newdeath}^-_{t-1} + \varepsilon t \quad \textit{(4b)}$$

$$\Delta\text{gold}_t=\vartheta_0+\sum\vartheta_1\Delta\text{gold}_{t-1}+\sum\vartheta_2\Delta\text{EPU}_{t-1}+\sum\vartheta_3\Delta\text{IDEMV}_{t-1}+\sum\vartheta_4\Delta\text{EMVI}_{t-1}+\sum\vartheta_5\Delta\text{VIX}_{t-1} +\sum\vartheta_6\Delta\text{totalcase}_{t-1}+\sum\vartheta_7\Delta\text{newcase}^+_{t-1}+\sum\vartheta_8\Delta\text{newcase}^-_{t-1}+\sum\vartheta_9\Delta\text{newdeath}^+_{t-1} +\sum\vartheta_{10}\Delta\text{newdeath}_{t-1}+\zeta_1\text{gold}_{t-1}+ \zeta_2\text{EPU}_{t-1}+ \zeta_3\text{IDEMV}_{t-1}+ \zeta_4\text{EMVI}_{t-1}+ \zeta_5\text{VIX}_{t-1}+ \zeta_6\text{totalcase}_{t-1}+ \zeta_7\text{newcase}^+_{t-1}+ \zeta_8\text{newcase}^-_{t-1}+ \zeta_9\text{newdeath}^+_{t-1}+ \zeta_{10}\text{newdeath}^-_{t-1} + \varepsilon t \quad \textit{(4c)}$$

After confirming the presence of the long-run cointegration between the variables, the long-run asymmetric effect of newcase, newdeath on gold (oil, stock) prices was examined. Several robustness tests were applied, including residual independence (autocorrelation), residual heteroscedasticity, and residual normality, to check the validity of the results (Çıtak et al., 2020).

3.2. Data Set

The asymmetric effect of the factors that cause price fluctuations in stock, oil, and gold markets during the Covid-19 Pandemic is examined in this study. The data set used for this purpose was divided into three groups. The first group used stock, oil, and gold prices as dependent variables to represent the investment tools. In the second group, new case numbers, new death numbers, and total case numbers worldwide were used to evaluate the effects of the COVID-19 pandemic. In the third group, to represent market uncertainties, the economic uncertainty index (EPU) and stock market uncertainty index (EMVI); for the volatility of investors' market expectations, the fear index (VIX) and to evaluate the effect of news about infectious diseases, the IDEMV index were used. The study conducted all analyses with 541 daily data sets between January 22, 2020, and March 16, 2022. Thus, the data set used is as in Table 1.

Table 1. Definitions and Data Sources of the Variables

Variable	Description	Source
STOCK	DJGI was used for the stock market in this study. Indexes for the United States, Canada, Japan, Hong Kong, Singapore, and Australia/New Zealand are constructed to cover 95% of market capitalization at the country level. The DJGI family includes indexes for 10 economic industries, 19 Supersectors, 41 sectors, and 114 subsectors. The indexes are reviewed quarterly.	www.investing.com
OIL	Crude Oil Prices: Brent - Europe, Dollars per Barrel, Daily, Not Seasonally Adjusted	World Bank Database
GOLD	Ounce price of gold	World Bank Database
EPU	This index was constructed to measure policy-related economic uncertainty by Baker, Bloom and Davis.	www.policyuncertainty.com
IDEMV	Infectious Disease Equity Market Volatility is a newspaper-based index constructed by Baker, Bloom, Davis, and Kost (2019).	www.policyuncertainty.com
EMVI	Index of Equity Market Uncertainty was constructed through an analysis of newspaper articles containing terms related to equity market uncertainty.	www.policyuncertainty.com

Table 1. Definitions and Data Sources of the Variables (Continue)

Variable	Description	Source
VIX	Chicago Board Options Exchange (CBOE) Volatility Index (VIX): a real-time market index that represents the market's expectation for 30-day forward-looking volatility.	www.investing.com
TOTALCASE	Number of total global cases of confirmed Covid-19 infections	European Center for Disease Prevention and Control (ECDC)
NEWCASE	Number of new global cases of confirmed Covid-19 infections	European Center for Disease Prevention and Control (ECDC)
NEWDEATH	Number of new global deaths due to Covid-19	European Center for Disease Prevention and Control (ECDC)

Descriptive statistics values of all variables indicated in Table 1 are as in Table 2.

Table 2: Descriptive Statistics for Variables

	INVESTMENT TOOLS		
	STOCK	**OIL**	**GOLD**
Mean	487.674	57.111	1819.070
Median	511.020	59.120	1810.000
Maximum	580.270	123.640	2117.000
Minimum	292.310	-36.980	1494.000
Std. Dev.	71.598	20.962	101.750
Skewness	-0.591	-0.105	-0.149
Kurtosis	2.204	3.561	3.471
Jarque-Bera	45.801	8.043	7.028
Probability	0.000***	0.017**	0.029**
	VARIABLES OF COVID-19		
	TOTALCASE	**NEWCASE**	**NEWDEATH**
Mean	1.32E+08	631320	8322
Median	1.11E+08	480726	6792
Maximum	4.64E+08	4115811	18021
Minimum	557	0.000	0.00
Std. Dev.	1.22E+08	720203	4227
Skewness	0.793	2.666	0.173
Kurtosis	2.848	10.425	2.503
Jarque-Bera	57.269	1884.029	8.260
Probability	0.000***	0.000 ***	0.016**

Table 2: Descriptive Statistics for Variables (Continue)

UNCERTAINTY INDEX				
	EPU	**IDEMV**	**EMVI**	**VIX**
Mean	206.701	16.135	116.269	24.898
Median	167.230	13.880	81.450	22.540
Maximum	807.660	68.370	939.580	82.690
Minimum	22.250	0.000	8.130	12.910
Std. Dev.	132.383	10.885	114.201	9.892
Skewness	1.430	1.568	2.571	2.477
Kurtosis	4.953	6.456	13.278	11.426
Jarque-Bera	270.505	491.235	2977.787	2153.874
Probability	0.000 ***	0.000 ***	0.000 ***	0.000 ***

***, ** and * denote rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively.

According to the obtained results for investment tools in Table 2, the average stock price index is 487,674, the average oil price is 57.111$, and the average gold price is 1819.07 $. Gold prices have the highest standard deviation, and oil prices have the lowest standard deviation. The skewness values obtained for stock, oil, and gold are negative, and the series is slanted to the left. Kurtosis values are positive, and the series is leptokurtic. In addition, none of the price series of investment tools has a normal distribution. According to the results obtained for uncertainty indices, the EPU index has the highest average value, and the IDEMV has the lowest average value. The uncertainty indicator with the highest standard deviation is EPU, and the lowest is VIX. The skewness and kurtosis values obtained for all uncertainty indices are positive, and the series is slanted to the right and leptokurtic. In addition, none of the uncertainty indices has a normal distribution. According to the results obtained for the COVID-19 variables, the average new case number is 631.320, and the average new death number is 8322. The skewness and kurtosis values for the COVID-19 variables are positive, indicating that the series is slanted to the right and leptokurtic. According to Jargue-Bera statistics, all COVID-19 variables do not have a normal distribution.

According to the Jarque-Bera test results from Table 2, all variables (oil, gold, new death) do not have a normal distribution at a 1% significance level. This result also supports the conclusion that the variables have a nonlinear distribution. It supports that nonlinear estimation methods are suitable for these variables (Anwar et al., 2021; Chien et al., 2021; Godil et al., 2021). Therefore, the nonlinear ARDL (NARDL) model is suitable for examining the cointegration relationship among the variables. However, the NARDL model also has a vital limitation regarding unit root results. This limitation is that the variables used in the study are not I(2), because cointegration occurs where the F-statistics are invalid if a variable becomes stationary at the second difference (Meo et al., 2018). In addition, the variables' unit root results are significant to avoid spurious outcomes. For that reason, the unit root test analysis of the variables used in the study was carried out with the Augmented Dickey-Fuller (ADF) unit root test. Accordingly, the ADF unit root test results of the variables used in the study are given in Table 3.

Table 3. Results of Unit Root Test

LEVEL				
	INTERCEPT		**INTERCEPT AND TREND**	
	t-Stat.	**Prob.**	**t-Stat.**	**Prob.**
STOCK	-0.923	0.781	-2.1234	0.531
OIL	-0.590	0.869	-3.919	0.011**
GOLD	-2.814	0.056*	-2.777	0.206
EPU	-3.036	0.032**	-4.307	0.003***
IDEMV	-3.930	0.002***	-4.921	0.000***
EMVI	-4.243	0.000***	-5.139	0.000***
VIX	-3.222	0.019**	-3.777	0.018**
TOTALCASE	3.547	0.980	1.756	0.980
NEWCASE	-0.971	0.764	-2.253	0.458
NEWDEATH	-2.730	0.069*	-2.347	0.407
FIRST DIFFERENCE				
	INTERCEPT		**INTERCEPT AND TREND**	
	t-Stat.	**Prob.**	**t-Stat.**	**Prob.**
STOCK	-13.979	0.000***	-13.966	0.000***
OIL	-21.519	0.000***	-21.561	0.000***
GOLD	-23.393	0.000***	-23.380	0.000***
EPU	-21.553	0.000***	-21.540	0.000***
IDEMV	-18.426	0.000***	-18.416	0.000***
EMVI	-18.204	0.000***	-18.187	0.000***
VIX	-30.161	0.000***	-30.137	0.000***
TOTALCASE	-2.847	0.052*	-4.231	0.004***
NEWCASE	-7.265	0.000***	-7.308	0.000***
NEWDEATH	-7.754	0.000***	-7.936	0.000***

*** ,**, * represents the level of significance at 1%, 5%, and.10% levels, respectively.

According to Table 3, while gold, death, EPU, EMVI, VIX and IDEMV are stationary in fixed form, all other variables become stationary when the first difference is taken. In fixed and trend ADF results, oil, EPU, EMVI, VIX and IDEMV are stationary, while all other variables become stationary at the first difference. These results also confirm that no variable is stationary in I(2), which is an essential restriction for implementing the NARDL model.

4. Empirical Results

The NARDL model is used in the study to examine long-term correlation, and long-term coefficients are estimated. In addition, diagnostic tests such as the Breusch-Godfrey LM test for serial correlation, ARCH and Breusch-Pagan-Godfrey test for heteroskedasticity, and Ramsey reset test for model specification are included to strengthen the model used.

4.1. Cointegration Analysis

Wald bound test is used to test the existence of long-term correlation among the variables. Accordingly, the F statistic values obtained for the NARDL model are as in Table 4.

Table 4. Results of Nonlinear ARDL Bound Test

INVESTMENT TOOLS	F-STATISTIC	DECISION
STOCK	31.675	Cointegration
OIL	3.698	Cointegration
GOLD	4.436	Cointegration
	K=9	
	UPPER BOUND	**LOWER BOUND**
10%	2.8	1.8
5%	2.08	2.04
1%	3.68	2.5

***, **, *, indicates statistical significance at 1%, 5% and 10% respectively.

According to Table 4, the F statistics value estimated for the NARDL model is higher than the upper bound values for stock, oil and gold. Therefore, a high F-statistics value provides enough information to reject the null hypothesis, which means there is no cointegration among the variables. In other words, there is a long-term cointegration between stock, oil and gold prices and NEWCASE_POS, NEWCASE_NEG, NEWDEATH_POS, NEWDEATH_NEG, TOTAL CASE, EPU EMVI, VIX and IDEMV. Here “pos” values indicate the increase, and “neg” values indicate the decrease. Accordingly, the long-term coefficients between these variables, which have a long-term relationship with stock prices, are estimated in Table 5.

Table 5. Results of Long-Term Coefficients for Stock Prices

	Coeff.	t-stats	Prob.
EPU	-0.023	-6.851	0.000***
IDEMV	-0.004	-1.655	0.098*
EMVI	0.001	0.741	0.459
VIX	-0.182	-30.972	0.000***
TOTALCASE	0.003	1.019	0.308
NEWCASE_POS	-0.031	-10.748	0.000***
NEWCASE_NEG	0.002	0.821	0.412
NEWDEATH_POS	0.006	1.841	0.066*
NEWDEATH_NEG	-0.028	-10.106	0.000***

***, **, *, indicates statistical significance at 1%, 5% and 10% respectively.

According to Table 5, EPU, IDEMV, VX, NEWCASE-POS, AND NEW DEATH-NEG values have a statistically significant negative effect on stock prices. In other words, the increase in economic policy uncertainty, the level of volatility, the pandemic-based news index, the number of new cases or the decrease in the number of new deaths cause the prices to decrease in stock markets in general. This result supports Ashraf (2020), Wang and Liu (2022), and Tuna and Tuna (2022)'s conclusions. This effect is most evident in the fear index. The decrease in the number of new cases, the increase in the number of new deaths, the increases in the number of total cases, or the increases in EMVI indices cause an increase in stock prices. However, the increases in the number of new deaths from these results are statistically significant, while the others are not. The most apparent effect of the increase in stock prices is the increase in new deaths. According to Table 5, stock prices negatively react to all uncertainties and fluctuations in the market. The increase in the number of new cases in the stock market during the COVID-19 pandemic decreased investors' interest in the financial markets and caused the prices to fall. However, while the decrease in cases causes the prices to rise in the stock markets, this effect is not as obvious as the decrease.

Oil prices are another essential tool for financial markets, and the long-term coefficients for these variables are as in Table 6.

Table 6. Results of Long-Term Coefficients for Oil Prices

	Coeff.	t-stats	Prob.
EPU	-0.070	-3.775	0.000***
IDEMV	0.008	0.617	0.538
EMVI	-0.017	-1.854	0.064*
VIX	-0.211	-6.498	0.000***
TOTALCASE	0.067	3.786	0.000***
NEWCASE_POS	0.016	1.033	0.302
NEWCASE_NEG	0.044	2.933	0.004***
NEWDEATH_POS	-0.194	-11.136	0.000***
NEWDEATH_NEG	-0.236	-15.532	0.000***

***, **, *, indicates statistical significance at 1%, 5% and 10% respectively.

According to Table 6, EPU, EMVI, VIX, NEW DEATH-POS, and NEW DEATH-NEG values negatively affect oil prices. Only the number of total cases has a positive, statistically significant effect. According to this result, the reaction of oil prices to positive and negative changes in the number of deaths due to the COVID-19 pandemic is negative. In other words, the change in the number of deaths has a reducing effect on oil prices. While the decrease in the number of cases leads to an increase in oil demand, it leads to an increase in prices. These results support Tuna and Tuna (2022), Al-Awadhi et al. (2020) and Ashraf (2020)'s conclusions.

The long-term coefficients of gold, which is always preferred by investors as a safe investment tool and which has an increasing popularity in all periods, with the examined variables are as in Table 7.

Table 7. Results of Long-Term Coefficients for Gold Prices

	Coeff.	t-stats	Prob.
EPU	0.005	1.072	0.284
IDEMV	-0.009	-3.106	0.002***
EMVI	0.004	1.864	0.063*
VIX	0.025	3.187	0.002***
TOTALCASE	0.073	17.381	0.000***
NEWCASE_POS	0.031	8.376	0.000***
NEWCASE_NEG	0.018	4.992	0.000***
NEWDEATH_POS	-0.061	-14.623	0.000***
NEWDEATH_NEG	-0.040	-11.189	0.000***

***, **, *, indicates statistical significance at 1%, 5% and 10% respectively.

According to Table 7, gold prices are statistically significantly affected by all the examined variables except for the EPU. While EUI and VIX positively affect gold prices, the IDEMV index affects them negatively. This also supports Bentes, Gubareva, and Teplova (2022)'s conclusions. At the same time, this result can be evaluated as increasing uncertainty in financial markets, causing an increase in the demand for gold, a safe investment tool, and, therefore, an increase in prices. While both increases and decreases in the number of new cases in variables of the COVID-19 pandemic have a positive effect on gold prices, changes in the number of new cases have a negative effect. This can be considered as an indicator that the announcement of the number of cases caused fluctuations in the market. Therefore, investors turned to a search for a safe haven, and the demand for gold increased.

4.2. Robustness Checks

Some analyses were used to strengthen the validity of the study results obtained with the NARDL model applied. The Breusch-Godfrey LM test was used for the serial correlation test, the Breusch-Pagan-Godfrey and ARCH test was used for the heteroskedasticity problem, and the Ramsey Reset Test was used to test the model suitability. Accordingly, the results obtained are shown in Table 8.

Table 8. Diagnostic Tests

Result of Diagnostic Tests for Used Models				
		Stock Prices	**Oil Prices**	**Gold Prices**
Test	**Problem**	**P-Value**	**P-Value**	**P-Value**
LM test	Serial Correlation	0.7648	0.3873	0.9778
Breusch-Pagan-Godfrey	Heteroskedasticity	0.6711	0.2923	0.1025
ARCH	Heteroskedasticity	0.6353	0.1736	0.7081
Ramsey Reset Test	Model Specification	0.2676	0.7262	0.9163

Table 8 shows no serial correlation according to the LM test results in the models in which the long-term relationship between stock, oil and gold prices and the selected uncertainty and Covid-19 variables are examined. In addition, the applied models have no heteroskedasticity problem according to both the Bresch-Pagan-Godfrey test and ARCH test results. Established model specifications are also correct according to Ramsey Reset Test.

5. Conclusion and Policy Implications

The COVID-19 pandemic is a significant risk factor for financial markets. Therefore, investors and theoreticians would like to know the effect of the COVID-19 pandemic on financial markets. Thus, they aim to increase the ability to predict risk, an important decision criterion in new investment decisions. The asymmetric effect that emerged due to the COVID-19 pandemic in the gold, oil, and stock markets, which constitute an essential part of the financial markets, is examined in this study. In addition, it aims to contribute to the literature by taking into account the results of the studies calculated by taking into account the gold, oil, and stock markets, as well as various uncertainties and pandemic-related factors. This study contributes to the current literature on three points. Firstly, the asymmetric effect of the COVID-19 pandemic could be examined using the NARDL model. Secondly, the reaction of financial markets to uncertainty factors was measured with the EPU, IDEMV, EMVI, and VIX indices, which were calculated by considering different factors. Oil, gold, and stock markets must also examine the correlation between Covid-19 and uncertainty indices. Gold, oil, and stock markets are the markets with relatively high transaction volume and with the tools most investors prefer.

According to the study results, stock markets are negatively affected by the increase in the number of new cases of COVID-19 and the increase in uncertainty. However, while oil prices reduce as the uncertainty increases, they positively react to all increases and decreases in the number of COVID-19 cases, and the prices increase. However, the general level of oil prices reacts to the increase and decrease in the number of COVID-19 deaths by decreasing. While gold prices are only negatively affected by the number of deaths due to COVID-19, they increase depending on the increase in uncertainty and the increase in the number of new cases.

This study presents essential conclusions for policymakers and other shareholders. The COVID-19 pandemic, a severe health threat to society, generally causes stock prices to decrease; however, gold and oil prices increase. This result is also supported by different uncertainty indices used in the study. While the increase in uncertainty in the financial markets causes the stock and oil prices to decrease, it causes the gold prices, which is the investor's safe haven, to increase. This result supports the conclusion that the events that may cause significant market fluctuations affect the financial markets differently. In addition, if portfolio managers and investors develop investment strategies by considering this situation, they can effectively manage risk.

Abbreviations

EPU: Economic policy uncertainty.

EMVI: Index of Equity Market Uncertainty.

VIX: Volatility Index.

IDEMV: Infectious Disease Equity Market Volatility.

NARDL: Nonlinear Autoregressive Distributed Lag.

Availability of Data and Materials

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Competing Interests

The author declares that he or she has no competing interests.

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