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# The Symmetric and Asymmetric Time-Varying Causality Relationships Between the COVID-19 Outbreak and the Stock Exchange: The Case of Selected Countries

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**Abstract:** In this study, the effects of COVID-19 (mortality rate, case rate, and bed capacity) on the stock market was examined within the framework of the efficient market hypothesis. Unlike other studies in the literature, we used the variable of bed capacity besides the mortality rate and case rate variables. The relationship between the mentioned variables, using daily data between December 31 of 2019 and November 10 of 2020, has been analyzed with time-varying symmetric and asymmetric causality tests for China, Germany, the USA, and India. Considering that the responses to positive and negative shocks during the pandemic process may be different and that the results may change depending on time, time-varying symmetric and asymmetric causality tests were used. According to the time-varying symmetric causality test, stock markets in all countries were affected in the period when the cases first appeared. A causal relationship between COVID-19 and country stock markets was found. The results showed that the effects of the case rate and bed capacity on the stock market occurred around the same time in Germany and the United States; however, these dates differed in China and India. According to time-varying asymmetric causality test findings, the asymmetric effect of the pandemic on the stock market in countries emerged during the second wave. The findings showed that the period during which positive and negative information about the pandemic intensified coincided with the period during which the second wave occurred; besides, the results show the effect of this information on the stock market differed as positive and negative shocks.

**Keywords:** COVID-19, Symmetric Relationships, Asymmetric Relationships, Efficient Market Hypothesis.

## Introduction

A new type of coronavirus called COVID-19 first appeared in Wuhan, China, in December 2019 and has caused great damage worldwide. Spreading at an alarming rate and infecting millions of people, the COVID-19 disease was declared a pandemic by World Health Organization (WHO) on March 11, 2020 (WHO, 2020). The data of the cases published by the WHO during the analysis period reveals a 4 times increase trend in number of cases worldwide. When the contagion process of the pandemic and the periods in which the cases increase are analyzed on a regional basis, the following dates and regions emerge: the first increase in the number of cases in the Western Pacific, which started on February 13; the second increase in cases on March 10 in Europe, the United States, the Eastern Mediterranean, the Western Pacific, Southeast Asia and Africa; the third beginning on August 1 in the United States, Southeast Asia, Europe, Africa, the Eastern Mediterranean and the Western Pacific; and the fourth beginning on November 6 in the EU, the United States, Southeast Asia, the Eastern Mediterranean, Africa and the Western Pacific. While China ranked first in the first increase in cases of the pandemic, Europe was first in the second increase, the USA in the third increase and again Europe in the fourth increase as the epicenter of the virus infections. As of November 10, 2020, there have been more than 50 million confirmed cases and 1,258,000 deaths in 208 countries, with the countries most affected by the pandemic being the United States, India, Brazil, Russia, France, Spain, Argentina, England, Colombia, and Mexico (WHO, 2020).

The spread of the coronavirus between countries has prompted many governments to take unprecedented measures to contain the pandemic. These measures have caused turmoil, erosion of confidence, and increased uncertainty in financial markets. As a result, the rate of market risk aversion has increased in a way that is unprecedented since the global financial crisis of 2008 (OECD, 2020). Investors are more optimistic when the market is in an upward trend and the perceived risk is reduced; when the market trends downwards, investors tend to be more pessimistic. This situation shows that investors' emotions play an important role in stock markets (Liu, et al., 2020).

The information provided is effective for guiding investors' emotions; it can provide signals to help in making investment decisions. The information provided concerning events can be perceived as positive, negative, or neutral news. This is because investors and businesses use this information to describe both past and future market conditions. Completeness, accuracy, and timeliness of information are important. The sooner the information is reflected in stock prices, the more efficient the stock market will be. The stock price adjusts quickly as new information becomes available and is absorbed by investors. Market efficiency is determined by the speed at which investors can respond to information (Machmuddah, et al., 2020).

Fama (1970) classified market efficiency as weak, medium strong, and strong forms. According to Fama, the inability to use past prices in future price estimates indicates the weak form of that market, the full reflection of publicly available information on stock prices indicates its medium strong form, and the reflection of all public and private sector information on stock prices makes up the strong form.

In this context, it is important to examine the effect of the information released about COVID-19 worldwide on the stock market. According to the information announced in the worldwide about the COVID-19 outbreak, stock markets were indeed affected. Whether the measures taken to combat the virus would be effective or the vaccine would be found had different effects on the stock market (Wagner, 2020).

This differentiation is manifested in negative and positive shocks on the stock market. Several studies in literature have examined the relationship between the COVID-19 pandemic and the stock market (e.g., Al-Awadhi, et al., 2020; Ashraf, 2020; Baker, et al., 2020; Lyócsa, et al., 2020; Mishra, et al., 2020; Narayan, et al., 2020; Okorie & Lin, 2020; Sharif, et al., 2020; Zhang, et al., 2020; Topcu & Gülal, 2020, Alfaro, et al., 2020; Zeren & Hızarcı, 2020; Gormsen & Koijen, 2020; Onali, 2020; and Erdem, 2020). In these studies, the effect of COVID-19 on the stock market was examined for case and death rates. However, the most important factor in combating the pandemic has been the strength of the health care system. Countries with strong health systems show rapid reflexes against the pandemic; they have prevented its spread with effective treatment methods. Conversely, the prolonging of the process of combating the pandemic in countries with weak health care systems caused devastating effects in many areas, especially economically and financially. In this respect, the strength of the health care system is one of the important indicators for the preparedness of a country to fight the pandemic. In line with this information, in addition to the mortality rate and case rate variables used in the literature, bed capacity is also considered an indicator for the strength of a country's health care system.

The effect of COVID-19 on the stock market varies according to the successes and failures in fighting the pandemic. The method used here allows the detection of negative shocks (positive: decrease in the number of cases and death toll) and positive shocks (negative: increase in the number of cases and death toll) as positive shocks (increase in the stock market) and negative shocks (decrease in the stock market), respectively, during the COVID-19 pandemic period. However, tests developed for causality analysis (Hacker & Hatemi, 2006; Hsiao, 1981; Sims, 1972; Toda & Yamamoto, 1995) accept that the effect of positive shocks is the same as the effect of negative shocks. However, in financial markets, in the presence of asymmetric information and the heterogeneity of market participants, positive and negative shocks of the same magnitude do not draw similar reactions. In this case, the results obtained from the aforementioned tests can be misleading.

The aim of the study is to determine the effect of the pandemic on the stock market by using the variables of case (case rate), death (mortality rate) and bed (bed capacity) and to reveal whether the effect of the pandemic on the stock market changes over time. In this way, it will be revealed whether the bed capacity, which is one of the important indicators of the severity of the pandemic, affects the stock market and when and how the impact of the pandemic on the stock market begins.

This study contributes to the existing literature, since, unlike many other studies, it covers a wider time period and analyzes bed capacity in addition to mortality rate and case rate variables. In addition, in examining the effect of the pandemic on the stock market in other studies, the data set of the analysis period is considered as a whole; in this study, it is examined by sub periods to take into account whether or not the said effect has changed in line with the new information announced.

The first part of the study includes data and methods used; the second part consists of empirical results; whereas the third part presents the conclusion and suggestion for future studies.

## Data and Methods

### *Data*

In this study, the daily data set of the COVID-19 outbreak and stock closing prices were used. A delay was taken for the variables (death, case, and bed) used for COVID-19, considering Ashraf's (2020) study. The time frame for the data is between December 31, 2019 and November 10, 2020. The variables are used in logarithmic form. Four countries, namely, the United States, Germany, China, and India, were selected for the study. Some criteria have been considered in the selection of these countries. The first of these criteria is made according to the development levels of the countries. Accordingly, the United States and Germany are in the developed country group, and China and India are in the rising economy group. A classification was made to assess whether the bed capacity is sufficient for the increasing number of cases in these countries, as an indicator of the strength of the health care system. According to this classification, the higher number of cases in some countries (USA and India) and the lower numbers in others (China and Germany) were considered. The information about the data appears in Table 1; descriptive statistics are included in Table 2.

**Table 1**
Summary of the Data

| Variables | Explanation | Source |
|---|---|---|
| Stock | Stock market closing prices | Investing. com |
| Death | Mortality rate = Number of deaths / Number of cases | (European Centre for Disease Prevention and Control, 2020) |
| Case | Case Rate = Number of cases / Total population | (European Centre for Disease Prevention and Control, 2020) |
| Bed | Bed Capacity = Number of beds / Number of cases | (World Bank, 2020)/ (European Centre for Disease Prevention and Control, 2020) |

**Table 2**
Descriptive Statistics

| | China | | | | Germany | | | |
|---|---|---|---|---|---|---|---|---|
| | **Stock** | **Death** | **Case** | **Bed** | **Stock** | **Death** | **Case** | **Bed** |
| **Mean** | 3071.7 | 0.1555 | 2.17E-07 | 685768.5 | 12000.4 | 0.2522 | 1.06E-05 | 148055.5 |
| **Med.** | 3019.5 | 0.0487 | 2.09E-08 | 205986.9 | 12488.4 | 0.0463 | 4.88E-06 | 1638.424 |
| **Max.** | 3451.1 | 2.0000 | 1.06E-05 | 6179608. | 13789.0 | 1.0000 | 7.42E-05 | 664153.7 |
| **Min.** | 2660.2 | 0.0000 | 6.97E-10 | 408.1104 | 8441.71 | 0.0007 | 1.20E-08 | 107.8697 |
| **S. D.** | 218.29 | 0.2780 | 8.44E-07 | 1442015. | 1362.17 | 0.3879 | 1.54E-05 | 267038.9 |
| **Skew.** | 0.1394 | 3.0207 | 9.117112 | 3.147361 | -0.72649 | 1.3408 | 2.233847 | 1.363985 |
| **Kurt.** | 1.5995 | 14.007 | 106.6378 | 11.97060 | 2.46304 | 2.9269 | 7.651700 | 2.944571 |
| **J-B.** | 18.353 | 1418.9 | 99659.51 | 1080.857 | 17.1963 | 51.570 | 298.1233 | 53.35509 |
| **Prob.** | 0.0001 | 0.0000 | 0.000000 | 0.000000 | 0.00018 | 0.0000 | 0.000000 | 0.000000 |
| **Sum** | 663493.2 | 33.593 | 4.69E-05 | 1.48E+08 | 2064060. | 43.377 | 0.001828 | 25465542 |
| **Obs.** | 216 | 216 | 216 | 216 | 222 | 222 | 222 | 222 |
| | **USA** | | | | **India** | | | |
| | **Stock** | **Death** | **Case** | **Bed** | **Stock** | **Death** | **Case** | **Bed** |
| **Mean** | 3146.91 | 0.1973 | 9.01E-05 | 6098.827 | 36583.13 | 0.2268 | 1.92E-05 | 152527.0 |
| **Med.** | 3237.18 | 0.0286 | 8.16E-05 | 1.320066 | 37981.63 | 0.0247 | 6.52E-06 | 81.27962 |
| **Max.** | 3580.84 | 1.0000 | 0.000369 | 35454.33 | 42597.43 | 1.0000 | 7.16E-05 | 724201.4 |
| **Min.** | 2237.40 | 0.0053 | 3.04E-09 | 0.292014 | 25981.24 | 0.0100 | 7.32E-10 | 7.397812 |
| **S. D.** | 282.778 | 0.3552 | 7.41E-05 | 12929.00 | 4115.882 | 0.3876 | 2.26E-05 | 286744.4 |
| **Skew.** | -1.02993 | 1.7305 | 0.57664 | 1.763469 | -0.574402 | 1.4484 | 0.803949 | 1.447139 |
| **Kurt.** | 3.45603 | 4.1427 | 3.09765 | 4.218223 | 2.140034 | 3.1733 | 2.161314 | 3.166718 |
| **J-B.** | 40.6155 | 121.22 | 12.2239 | 127.0506 | 18.96265 | 77.548 | 30.28374 | 77.39272 |
| **Prob.** | 0.00000 | 0.0000 | 0.00221 | 0.000000 | 0.000076 | 0.0000 | 0.000000 | 0.000000 |
| **Sum** | 689173.6 | 43.213 | 0.01973 | 1335643. | 8084871. | 50.127 | 0.004243 | 33708464 |
| **Obs.** | 219 | 219 | 219 | 219 | 221 | 221 | 221 | 221 |

A two-stage process was followed to examine the dynamic relationships between COVID-19 and stock market variables. In the first stage, a time-varying symmetric causality test based on Hacker and Hatemi-J's (2006) research was performed, whereas in the second stage, a time-varying asymmetric causality test developed according to Hatemi-J (2012) was performed.

*Time-Varying Causality Tests*

Many structural changes, such as economic and political events, can take the relationship between variables to different dimensions. For this reason, many authors (such as Arslantürk, et al., 2011; Balcılar & Özdemir, 2013; Inglesi-Lotz, et al., 2014; Yılancı & Bozoklu, 2014; Zeren & Koç, 2016; Jammazi, et al., 2017; Kanda, et al., 2018; Erdoğan, et al., 2019) have emphasized the importance of time-varying analysis methods when examining the relationships between macroeconomic variables.

Because of the traditional VAR model framework, commonly used test statistics such as the Wald, likelihood ratio (LR), and Lagrange multiplier (LM) test used to measure Granger causality can have nonstandard asymptotic properties if variables considered in VAR are integrated or cointegrated. To overcome this problem, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) proposed a solution that guarantees standard asymptotic distribution for Wald tests performed on coefficients of VAR (p) processes where variables are at the level of I (1). These solutions require that at least one coefficient matrix be unconstrained under the null hypothesis. The time-varying causality test used in the present study is based on the bootstrap causality test developed by Hacker and Hatemi-J (2006) based on the causality test of Toda and Yamamoto (1995). In order to test bootstrap LR Granger causality, the bivariate basic VAR (p) model was defined as follows (Balcilar, et al., 2010):

$$y_t = \hat{\mu}_0 + \hat{\mu}_1 y_{t-1} + \ldots + \hat{\mu}_p y_{t-p} + \varepsilon_t, \quad t = 1, 2, \ldots, T$$

(1)

In the model, while n-dimensional vectors, was expressed as the n × n matrix of the parameters obtained for p delay, defined the nonsingular covariance matrix and the zero-mean independent white noise process. Here the p lag length was determined according to Akaike Information Criteria (AIC).

Toda and Yamamoto (1995) proposed an extended VAR (p + d) model to test the causality relationship between integrated variables:

$$y_t = \hat{\mu}_0 + \hat{\mu}_1 y_{t-1} + \ldots + \hat{\mu}_p y_{t-p} + \hat{\mu}_{p+d} y_{t-p-d} + \hat{\varepsilon}_t, \quad t = 1, 2, \ldots, T$$

(2)

In the model, *p* represented the optimal lag length, and *d* represented the maximum degree of integration. Before making an estimate, some definitions were made for the sample size *T*. Here the matrix matrix is expressed as follows:

$$Z_t := \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ \vdots \\ y_{t-p-d+1} \end{bmatrix}, \ \left(1 + n(p+d)\right) \times 1) \ \text{ matrix } t = 1, 2, \ldots, T \quad Z := \left(Z_0, \ldots, Z_{T-1}\right),$$

$\left(1 + n(p+d)\right) \times 1)$ and $\hat{\delta} := \left(\hat{\varepsilon}_1, \ldots, \hat{\varepsilon}_T\right)$, $(n \times T)$ was defined as the matrix; in line with this information, the VAR$\left(p+d\right)$ model estimated could be expressed as follows:

$$Y = \hat{D}Z + \hat{\delta} \tag{3}$$

In summary, the modified Wald test (MWALD) by Toda and Yamamoto (1995) to test Granger causality between variables was defined as follows:

$$MWALD = \left(C\hat{\beta}\right)' \left[C\left(\left(ZZ'\right)^{-1} \Theta S_U\right)C'\right]^{-1} \left(C\hat{\beta}\right)$$

(4)

In the equation, Θ, the Kronecker factor, and make up a matrix. as and Hacker and Hatemi-J (2006) suggested that if the MWALD test, which has an χ2 distribution, were performed by using the bootstrap technique, it could eliminate some problems (such as misleading results if the correct size was not provided in a finite sample). Thus, more reliable critical values could be obtained, and deviations in estimation could be reduced.

The basis of the causality method that changes over time was the method developed by Hacker and Hatemi-J (2006). However, although Hacker and Hatemi-J (2006) took into account the entire sample in the causality test, the subperiods of the sample were taken into account in the causality test that changed over time. Thus, a causality test was applied to each subperiod.

The important factor in this method was to determine the length (number of windows) of the subperiod as stated by Brooks and Hinich (1998). Accordingly, the number of windows was determined based on Caspi's (2017) study. The number of windows of the study was determined to be 29 when using the formula T (0.01 + 1.8 / √T).

Then, the following stages were followed for the implementation of the method: in the first stage, the Hacker and Hatemi-J (2006) causality test was applied for the interval from the first observation to the 29$^{th}$ observation. In the second stage, the first observation was discarded; this test was applied to the observation interval with the second observation (29 + 1), and the test was continued until the last observation in the data range was used by making the first observation at each new stage and adding a new observation to the last observation. To test the significance of these results, the test statistic obtained at each observation interval was normalized with the bootstrap critical value. The point to be emphasized here is that not only the Wald test statistics but also the bootstrap critical values changed with time. Therefore, the test statistic obtained at each observation interval would be normalized with the 10% bootstrap critical value obtained during this observation interval. The periodic test statistic value for each subperiod was calculated as follows:

$$\textit{Periodic test statistic value} = \frac{\textit{MWALD statistics calculated for any sub-period}}{\textit{10\% bootstrap critical values for any sub-period}} \qquad (5)$$

(5)

The values were plotted to interpret the resulting Wald test statistics. In this graph, there is a causality relationship between the periods when these test statistics values were greater than 1 (Erdoğan et al., 2019; Yılancı & Bozoklu, 2014).


**Graph 1**

Time Varying Symmetric Causality Test Results

Empirical Results: Time-Varying Symmetric Causality Test. According to the findings of the causality test, which changed over time, the stock markets were affected in all countries when the cases first appeared. The first official data on COVID-19 in China were cases on December 31 and deaths on January 11. However, the effects of COVID-19 on the stock market emerged about one month later. Based on the auxiliary variables used to measure the impact of the pandemic in China, a causality relationship was found on these dates for death (February 7–September 22), case (April 14–October 29) and bed (April 14–September 2). The first official data on COVID-19 in Germany were a case on January 28 and deaths on March 10. The effects of these variables on the stock market coincided with death (March 2–November 2), case (March 9–October 7), and bed (March 9–October 7). Therefore, it can be extrapolated that the German stock exchange is affected not only by country-specific news but also by news from other countries. The first official data on COVID-19 for the United States were case (January 21) and death (March 1). The reaction of the U.S. stock market to the pandemic coincided with the first official figures announced in China when the pandemic started. Thus, the causality relationship for the United States manifested as death (December 31–October 7), case (December 31–November 6), and bed (December 31–November 6). The first official data on COVID-19 for India were case (January 30) and death (March 13). The reaction of the Indian stock market to COVID-19 occurred instantly. Therefore, the causality relationship coincides with death (January 30–July 27), case (January 23–August 24), and bed (January 31–November 9). In addition, the causality relationship among countries differs in terms of bed capacity. Although the number of case and bed affected the stock markets of Germany and the United States on the same dates, these dates differed for China and India. The sudden increase in the number of case due to the pandemic in Germany and the United States compared with other countries and the relatively high elderly population affected how this situation manifested itself.

*Time-Varying Asymmetric Causality Test*

Tests developed for causality analysis (Hacker & Hatemi, 2006; Hsiao, 1981; Sims, 1972; Toda & Yamamoto, 1995) accept that the effect of positive shocks is the same as the effect of negative shocks. However, in financial markets, in the presence of asymmetric information and the heterogeneity of market participants, positive and negative shocks of the same magnitude do not draw similar reactions. In this case, the results obtained from the aforementioned tests can be misleading. It was first suggested by Granger and Yoon (2002) that the relationship between positive and negative shocks could differ from the relationship between variables. The researchers stated that the economic series are cointegrated when they react to shocks together; when they react separately, there cannot be a cointegration relationship between them. Therefore, they separated the data into cumulative positive and negative changes and examined the long-term relationship between these parts. Hatemi-J (2012) adapted the Granger and Yoon (2002) approach for causality analysis. The aim of this asymmetric causality test is to find the hidden structure that will help illustrate the dynamics of the series as in the cointegration analysis of Granger and Yoon (2002) and allow the development of predictions for the possible future. Hatemi-J (2012) defined the two series and, whose causality relationship is investigated, as follows:

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{\acute{Y}=1}^{t} \varepsilon_{1i}$$

**(1)**

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{\acute{Y}=1}^{t} \varepsilon_{2i}$$

(2)

and in the definition of the variable indicate their initial values, while and within the variables indicate the total shocks. These shocks are defined as follows:

$$\varepsilon_{1i}^{+} = \max(\varepsilon_{1i}, 0), \qquad \varepsilon_{1i}^{-} = \min(\varepsilon_{1i}, 0)$$
$$\varepsilon_{2i}^{+} = \max(\varepsilon_{2i}, 0) \qquad \varepsilon_{2i}^{-} = \min(\varepsilon_{2i}, 0) \tag{3}$$

The relationship can be indicated as and . If and variables are redefined, they become

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{Ý=1}^{t} \varepsilon_{1i}^{+} + \sum_{Ý=1}^{t} \varepsilon_{1i}^{-}$$
$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{Ý=1}^{t} \varepsilon_{2i}^{+} + \sum_{Ý=1}^{t} \varepsilon_{2i}^{-}$$

(4)

The positive and negative shocks in each variable are expressed in Equation (5) in the cumulative form.

$$y_{1i}^{+} = \sum_{Ý=1}^{t} \varepsilon_{1i}^{+}, \quad y_{1i}^{-} = \sum_{Ý=1}^{t} \varepsilon_{1i}^{-}, \quad y_{2i}^{+} = \sum_{Ý=1}^{t} \varepsilon_{2i}^{+}, y_{2i}^{-} = \sum_{Ý=1}^{t} \varepsilon_{2i}^{-}, \tag{5}$$

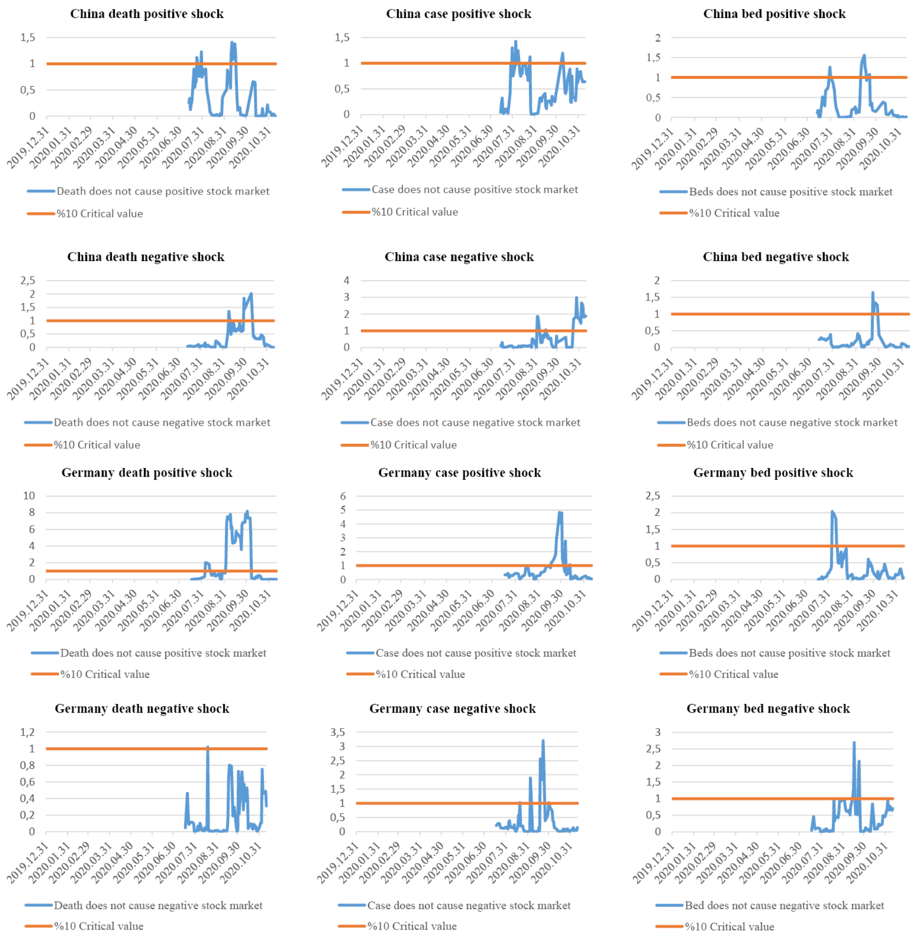
where indicates positive shocks of the first variable, indicates negative shocks of the first variable, indicates positive shocks of the second variable, and finally, indicates negative shocks of the second variable.

In this study, the stability of the causality relationship between positive and negative shocks will be tested using the time-varying form of the asymmetric causality test developed by Hatemi-J (2012). The subsample size for the asymmetric causality analysis that changes over time is 29, as in the symmetric analysis. Subsequent operations are repeated as in the symmetric analysis. In addition, the appropriate delay length in this study was decided using the information criterion contributed by Hatemi-J (2003), and an additional delay was added to the VAR model, which was determined according to this appropriate delay length, following the suggestion of Dolado and Lütkopohl (1996).

Empirical Results: Time-Varying Asymmetric Causality Test. The method used here allows the detection of negative shocks (positive: decrease in the number of case and death) and positive shocks (negative: increase in the number of case and death) as positive shocks (increase in the stock market) and negative shocks (decrease in the stock market), respectively, during the COVID-19 pandemic period. Although these positive and negative developments and their effects on negative and positive shocks of countries appear in detail in Appendix Tables A.1 and A.2, they are summarized here in general terms.

The positive developments experienced globally during the pandemic process generally cause positive shocks in the stock markets of the countries subject to analysis. The positive development experienced in this process are as follows: statements were made that serious progress has been made in vaccination studies, and with the discovery of new information about the structure of the virus, public awareness was raised regarding the importance of masks, hygiene, and maintaining distance in combating the virus.

Negative global developments caused negative shocks in the stock markets of some countries. These negative developments can be summarized as follows: the number of cases began to increase rapidly as countries loosened measures due to economic concerns, although a solution to the pandemic had not been found, and people did not take the virus seriously. With these increases, it was reported that a second wave would occur and that this would be even more severe. Concerns were raised about whether the proposed vaccines would be effective as well as what their side effects would be. Uncontrollable increases in the number of cases raised concerns that the health system would not be successful in combating the pandemic because of the insufficient number of beds, the inadequacy of health care workers, and the increase in the number of cases among health care professionals. The increases in the number of case and death increased fear among the people. In addition, one of the important developments that would cause these negative shocks was the U.S. president's statements that he would withdraw his support from the WHO because of the tension between the United States and the WHO.




**Graph 2**
Time Varying Asymmetric Causality Test Results


**Graph 2**
Time Varying Asymmetric Causality Test Results

The reasons for the positive and negative shocks experienced could stem from global developments as well as from country-specific developments during the pandemic process. These developments are summarized according to country (China, Germany, the United States, and India).

When the results of the asymmetric causality test were evaluated, it was revealed that while positive developments experienced on a global scale in the fight against the pandemic caused positive shocks for each country, the positive developments specific to the country also affected the positive shocks. Accordingly, China, the country where the pandemic first occurred, gained experience earlier than the other countries in combating the pandemic. The positive atmosphere caused positive shocks in this country to emerge earlier than in other countries.

Although negative shocks in China were expected to emerge in the early periods, it was observed that the negative atmosphere originating from China did not create a negative shock for the Chinese stock market during this period. Therefore, it could be argued that the negative shocks that occurred in China were not caused by specific negative shocks but by negative developments around the world. China, the world's most important exporting country, was able to cope with the pandemic in a short time. However, the negative atmosphere created by the global pandemic and the ensuing shrinking of the economies of the countries to which it exported were effective in creating the negative shocks on the Chinese stock market during this period. On a global scale, negative news such as the uncontrollable increase in the number of case and death, the increasing prospect that a perfect vaccine would not be possible, and the statement that Denmark would cull minks after the discovery of a new mutated coronavirus species could be given as the sources of negative shocks in China.

The positive shocks affecting Germany in the period subject to analysis stemmed from the positive developments in the world and Europe. This process coincided with the period when the severity of the pandemic decreased, and normalization steps were taken in European countries. These positive developments were mainly the result of EU countries' starting to relax their COVID-19 measures by opening their borders to 15 countries in early July, 2020. In addition, leaders of EU countries agreed to provide aid packages to reduce the devastating effects of the pandemic on the economy.

During the process of combating the pandemic in Germany, there were positive developments that created positive shocks, but also negative developments that caused negative shocks. The negative developments that caused negative shocks can be summarized as follows: an uncontrollable increase in the number of cases in Europe, problems with medical equipment (such as masks and respiratory devices), and the probability that the health system would not be successful in its struggle against the pandemic. In particular, the insufficient numbers of bed and health care professionals as well as the rise in cases among health care workers increased concerns.

In addition to the positive shocks arising from the positive developments in the world, the positive developments experienced specifically in the United States have been a source of these positive shocks. Some of the positive developments experienced specifically in the United States in the current periods can be summarized as follows: allowing plasma therapy for COVID-19 patients, the recovery of the U.S. president from the coronavirus, the U.S. Food and Drug Administration's (FDA) approval of the use of the antiviral drug Remdesivir in the treatment of COVID-19.

The negative developments that caused negative shocks can be summarized as follows: the United States ranking first in number of cases as a result of the rampant spread of the virus, problems related to medical equipment (such as masks and respiratory devices); general elections in the United States; expectations that the health care system would be unsuccessful in combating the pandemic due to the inadequate number of beds; the limited number of health care workers; and the escalation in the number of cases among health care professionals.

No positive developments occurred to create a positive shock specific to India. As in China, positive shocks in India stemmed from positive developments on the global scale. The pandemic emerged in India after China, Germany, and the United States, and the experiences of these countries in combating the pandemic (the effectiveness of some medicines in the treatment of the corona virus, the application of plasma therapy, etc.) were perceived as positive developments, causing the emergence of positive shocks.

The source of the negative shocks in India was the fear that the second worldwide wave would occur just as the pandemic was starting in the country. This would cause the number of cases to increase in a noticeably short time, and India would jump to second place in the number of cases after the United States. Therefore, the inadequacy of the current health care system increased negative expectations that India would not be able to prevent the number of cases from increasing.

Tests developed for causality analysis (Hacker & Hatemi, 2006; Hsiao, 1981; Sims, 1972; Toda & Yamamoto, 1995) accept that the effect of positive shocks is the same as the effect of negative shocks. However, in financial markets, in the presence of asymmetric information and the heterogeneity of market participants, positive and negative shocks of the same magnitude do not draw similar reactions. In this case, the results obtained from the aforementioned tests can be misleading. It was first suggested by Granger and Yoon (2002) that the relationship between positive and negative shocks could differ from the relationship between variables. The researchers stated that the economic series are cointegrated when they react to shocks together; when they react separately, there cannot be a cointegration relationship between them. Therefore, they separated the data into cumulative positive and negative changes and examined the long-term relationship between these parts. Hatemi-J (2012) adapted the Granger and Yoon (2002) approach for causality analysis. The aim of this asymmetric causality test is to find the hidden structure that will help illustrate the dynamics of the series as in the cointegration analysis of Granger and Yoon (2002) and allow the development of predictions for the possible future. Hatemi-J (2012) defined the two series Importar imagenand Importar imagen, whose causality relationship is investigated, as follows:

## Conclusion

In this study, the time-varying causality and asymmetric causality relationship between COVID-19 (case rate, mortality rate, and bed capacity) and stock market closing prices in selected countries (United States, Germany, China, and India) was investigated. We have analyzed this relationship, considering that it may change over time and that the responses to negative and positive shocks in the relevant variables may differ.

Two waves were noted by the WHO during the period under analysis. The date of the first wave of the pandemic fell to June, when countries entered a period of normalization; the second wave covered the period when the cases increased again after the normalization process.

In this study, the causality relationship between COVID-19 and the stock markets of selected countries was tested symmetrically and asymmetrically. According to the findings of the causality test that changes over time, the virus affected the stock markets in all countries when cases first appeared. We have found a causality relationship between the countries' stock markets and the auxiliary variables (death, cases, and beds) we used to measure the impact of COVID-19 in the countries included in the analysis. The study has also shown that the causality relationship changes over time, so the frequency and persistence of the relationship would also differ for distinct shocks. According to the asymmetric causality findings that change over time, the asymmetric effect of the pandemic on the stock market in countries emerged during the second wave. The effect of COVID-19 (case rate, mortality rate, and bed capacity) on the stock market changed over time in the countries subject to the analysis (except for the negative shock of the number of deaths in India).

The findings in other studies in the literature (Özparlak, 2020; Topçu & Gülal, 2020; Baek et al., 2020; Khan et al., 2020; Ashraf, 2020; Al-Awadhi et al., 2020; and He et al., 2020) were similar to those of this study. Zeren and Hızarcı (2020), Barut and Yerdelen Kaygın (2020), and Hacıevliyagil and Gümüş (2020) found a relationship between the stock markets of some countries and the cases and mortality, but not for other countries.

Although the findings in this study support the findings of other studies in the literature, the effect of COVID-19 on the stock market appeared to be short term. Given that the method used has a more advanced technique than the methods used in other studies, it reveals the reaction time to shocks and the type of shock, making the findings of this study remarkable. The major contribution of this study has been to examine whether psychological factors such as panic and fear that occur when the bed capacities of countries are insufficient in the face of increasing cases could influence the stock market. Thus, the periods in which this effect occurred (or not) were analyzed.

Besides the death (mortality rate) and case (case rate) variables used in the literature, when the effects of the information on bed capacity on the stock market were evaluated according to the efficient market hypothesis, it arose that whereas the reaction of the market to official information about COVID-19 was delayed in China, in other countries, its effect on the stock market was immediate. In line with this information, the stock markets of other countries have stronger structures than that of the Chinese market, which is in the medium-strong form.

As this study was carried out while the pandemic process and the effects continued, it could be analyzed by increasing the number of countries and diversifying financial and economic indicators in the subsequent studies.

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## Appendix

**Table A.1**
Positive shock dates

Note: * country-specific positive news

**Table A.2**
Negative shock dates

Note: * country-specific negative news