IJEFI
INTERNATIONAL JOURNAL OF ECONOMICS AND FINANCIAL ISSUES
EJ EconJournals
ISSN: 2146-4138

International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2024, 14(6), 320-326.

EJ EconJournals

The Impact of COVID-19 and Structural Market Changes on the Greek Stock Market: An Empirical Analysis

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Received: 14 May 2024 **Accepted:** 30 August 2024 **DOI:** https://doi.org/10.32479/ijefi.16759

ABSTRACT

This study examines the dual impact of COVID-19 and structural market changes on the Greek stock market, specifically the Athens stock exchange (ASE). Quantitative data analysis, granger causality models, and Hsiao's approach to granger causality were employed to investigate the causalities between COVID-19 pandemic measures and ASE returns. Our findings reveal that pandemic-related variables, including lockdown measures and mobility restrictions, significantly negatively affected the ASE by disrupting economic activities and diminishing investor confidence. Conversely, the study also highlights the positive impact of monetary policy interest rates on the market, which helped stabilize the financial environment by lowering borrowing costs and stimulating investment. These results underscore the intricate dynamics between crisis-induced restrictions and monetary policy adjustments, offering valuable insights for policymakers and investors navigating economic uncertainties.

Keywords: Athens Stock Exchange, COVID-19, Pandemic Impact, Unit-Root Test, Hsiao's Approach, Granger Causality
JEL Classifications: C32, E44, G14, G17

1. INTRODUCTION

The globalization and interconnectedness of economies increased the consequences of the COVID-19 pandemic on national economies, which already felt the repercussions of the internal profile related to the spread of coronavirus and the measures adopted for its restrictions. A harmful impact was seen across the board in the stock markets as a result of the proliferation of COVID-19, the implementation of movement restriction restrictions, and the rise of concerns regarding the state of the global economy (Chowdhury et al., 2021).

The beginning of the COVID-19 outbreak caused major unpredictability in stock markets across the world. As a result, the majority of global stock market indices have witnessed their worst 1-day declines ever, and there is not a single sector that has been immune to the aftermath. Contessi and De Pace (2020) presented statistical evidence of instability transmission from the Chinese stock market to all other markets between February and April of the year 2020. Fernandes (2020) analyzed the New York Stock Exchange (NYSE) and discovered that it had fallen by <30% from its peak in March 2020. He also monitored the movements of the stock market in other key nations across the world and documented that the results of the stock markets in the United Kingdom, Germany, Brazil, and Columbia were even worse than the performance that was documented in the NYSE. Alber (2020) used a panel data analysis to demonstrate that from 1 March 2020 to 10 April 2020, new cases of COVID-19 had a greater impact on the stock markets of China, France, Germany, and Spain than deaths. Kartal et al. (2021) investigated how key stock market indexes reacted to the COVID-19 pandemic in several East Asian countries, including China, Hong Kong, Japan, Mongolia, Korea, and Taiwan.

The outcomes of the quantile regression models illustrated the catastrophic effect that the epidemic had on the many marketplaces that were investigated. In a study conducted by Al-Awadhi et al. (2020) from 10 January 2020 to 16 March 2020 using a panel data approach, it was discovered that companies that were included in the Hang Seng index and the Shanghai stock exchange composite index were significantly negatively related to both the daily growth in total new cases and total new deaths caused by the coronavirus. Adenomon et al. (2020) in Nigeria reported a negative impact of the pandemic components on the stock market for the period encompassing 2 January 2020 and 16 April 2020, using the GARCH models. Abdelrhim and Elsayed (2020) utilized multiple regression analysis to investigate the impact that COVID-19 cases and fatalities had on Egypt's stock market across 17 distinct industries between March and May 2020. According to (Hui et al. (2020), new cases affected the Italian Stock Exchange (referred to as the Borsa Italiana) index, but new fatalities had no appreciable bearing on the pandemic variables. New cases of coronavirus are more significant than cumulative cases, and it seems that returns on stock markets are more sensitive to daily fatality rates than they are to cumulative mortality indices. Christodoulou-Volos and Tserkezos (2024) examined the impact of the COVID-19 outbreak on the Cypriot stock exchange (CSE) utilizing daily stock market returns from September 03, 2019, to July 10, 2020. They employed Granger causality models, particularly Hsiao's approach, to determine how the CSE is influenced by the novel coronavirus crisis. The findings reveal complex dynamics and significant volatility during the pandemic, highlighting the factors contributing to these fluctuations. Despite the pronounced volatility and shifts in market conditions, the CSE demonstrated resilience and an ability to recover during the initial shutdown period. Meher et al. (2022) examined the existence of a correlation between the stock prices of the energy sector, commodities prices of the energy sector, and market indices. The study uses an empirical approach to develop various VAR (vector autoregression) with variance decomposition models for each company under the energy sector indexed in NIFTY50 by considering daily prices for 3 years. For a comparative study, the data have been divided into two parts. The first part is considered pre-COVID era, i.e., from July 01, 2018, to December 31, 2019, and the second part is considered post-COVID era, i.e., from January 1, 2020, to June 30, 2021. While observing the estimates of VAR of different companies, it can be said that crude oil is significant in most of the models during pre-COVID whereas, during post COVID, lag term of crude oil and Niftyengergy are significant.

In order to stop the disease from spreading further, national authorities have implemented restrictions like travel bans, confinement, and lockouts. The response that has been given all across the world to the outbreak has been extraordinary. Because of this, the economies were significantly harmed as a result of the encouragement given to people to remain at home. The severity of the situation was felt in a variety of industries (i.e. tourism, hospitality, travel, sports, finance, environment, health, and education), which ultimately led to a reduction in gross domestic product (GDP). Using a panel approach, Ozili and Arun (2020) studied the impact that socially distant policies have on the stock market (as evaluated by leading stock market indicators of Japan, the United Kingdom, the United States, and South Africa). The primary findings suggested that the number of lockdown days and restrictions on overseas travel hurt the stock market from the 23rd of March 2020 to the 23rd of April 2020, however, the results indicated that internal movement restrictions influenced the market. Chowdhury et al. (2021), following the footsteps of Ozili and Arund (2020), expanded the analysis by including certain countries from Europe (Italy, Germany, and Spain) in a panel format identical to the one previously used. They revealed that factors such as the number of lockdown days, the number of new coronavirus patients, limits on internal movement, and international travel bans all affected the stock market.

During the COVID-19 outbreak, Zoungrana et al. (2021) concentrated on the stock returns of companies that were registered on the stock market of the West African Economic and Monetary Union (which includes Benin, Burkina Faso, Ivory Coast, Guinea- Bissau, Mali, Niger, Senegal, and Togo). They aimed to investigate how anti-COVID-19 initiatives implemented by the government impacted businesses in general as well as the sectors that are home to the majority of publicly traded companies (i.e., industry, finance, and distribution). Movement restrictions and lockdown measures were related to a negative reaction from the market, whereas social distance and governance measures were associated with a positive reaction from the market. The restrictions placed on stock movement had a severe influence on the stock values of companies operating in all three industries. However, corporations operating in the industry and financial sectors were struck more by the lockout measures than their distribution sector counterparts. Utomo and Hanggraeni (2021) also carried out an in-depth examination of the Indonesian stock market. They focused their attention on several companies operating in both general and specialized industries. In addition to the number of new cases and deaths caused by the COVID-19 pandemic, it was also concluded that the lockdown measures had a large impact on the stock market based on the findings of the fixed-effects panel regression. Upon examining businesses based on their sectors, it was found that those in certain sectors (such as basic industries, consumer products, mining, trade, service, and investment) were more significantly impacted by the economic downturn compared to businesses in other sectors (such as agriculture and infrastructure).

The impact of crude oil price fluctuations on a company's stock value has sparked considerable global economic discussion. As a key economic indicator, crude oil prices provide crucial signals to governments. The COVID-19 outbreak introduced unprecedented uncertainty, disrupting both oil and stock markets. Zhang and Hu (2020) analyzed the stock markets in the United States, Japan, and Germany from January to September 2020. They found that while all three countries' stock markets were trending toward normalcy by the end of the study period, they remained volatile due to the ongoing COVID-19 pandemic.

This study aims to investigate whether the frequency of new cases and deaths caused by the SARS-CoV-2 virus impacts the ASE index. We examine the ASE index changes over time concerning variables representing the spread of COVID-19 in Greece (number of new cases and deaths) and government actions (internal movement restrictions, international travel controls, and monetary policy measures). Ashraf (2020) demonstrated that newly implemented social distancing measures had a direct negative impact on stock market performance. Conversely, an improvement in stock market returns was observed indirectly when the number of confirmed COVID-19 cases declined. Quarantine policies, COVID-19 testing, and financial assistance packages positively impacted market results.

The rest of this paper is structured as follows. Section 2 presents data, and the research methods and discusses the empirical results. Finally, Section 3 presents a summary of this empirical research and some concluding results.

2. DATA, RESEARCH METHODS, AND EMPIRICAL RESULTS

The data used for this empirical study encompasses daily COVID-19 statistics and stock observations (ASE index) from GitHub and the Athens stock exchange (ASE), respectively, covering the period from March 11, 2020 (the first confirmed case of COVID-19 in Greece) to 28 October 2020 and 29 October 2020 to 30 April 2021. The objective of the analysis is to investigate the relationship between stock performance (Y_t) and various COVID-19 sub-variables (X_t), including COVID-related deaths, hospitalizations, ICU admissions, and daily reported new cases. The closing daily stock prices were utilized for the study.

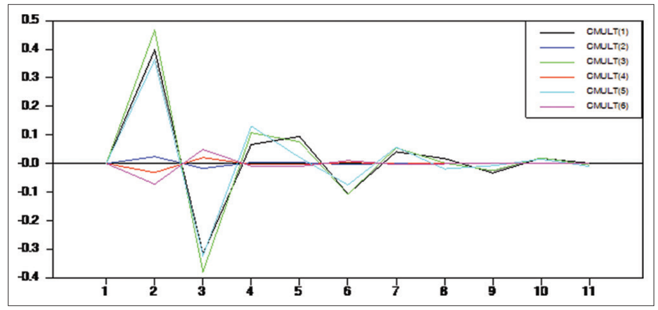
2.1. COVID-19 Data

In the aftermath of the global COVID-19 pandemic, comprehending the relationship between public health factors and financial markets has become increasingly important. The pandemic's widespread impact on economies highlights the need to study local stock market dynamics to gain valuable insights for investors, policymakers, and the public. This analysis examines the relationship between COVID-19 variables and stock performance in the Athens stock exchange general index (ASE), thereby enhancing our understanding of the interplay between public health and financial markets.

The dynamic effects analysis provided valuable insights into the relationship between COVID-19 variables and the portfolio performance index. Figures 1-3 depict the dynamic effects of the announcement of the number of COVID-19 cases, the number of COVID-19-intensive care units, and COVID-19 deaths on the portfolio of the ASE. These visual representations offer a clearer understanding of how changes in COVID-19 variables impact stock performance over time. The analysis revealed specific patterns and trends, shedding light on the sensitivity of the stock market to COVID-19-related developments. Figure 1 shows the dynamic effects of the announcement of the number of COVID-19 cases on the ASE.

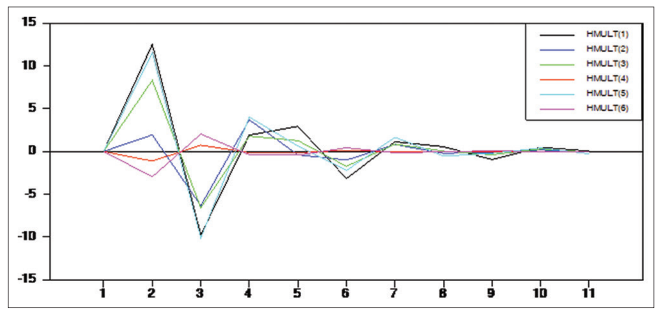
The impact of COVID-19 case announcements on stock market indices is a complex and multifaceted relationship. Firstly, these announcements can trigger fluctuations in market sentiment, as surges in cases often invoke fear and uncertainty among investors. This can lead to a sell-off of stocks, causing market declines. Secondly, rising case numbers can have a direct economic impact. Lockdowns and reduced economic activity, in response to higher cases, can affect company earnings and subsequently lead to declines in stock prices. Additionally, certain sectors, such as

Figure 1: The dynamic effects of the announcement of the number of COVID-19 cases on the Athens stock exchange



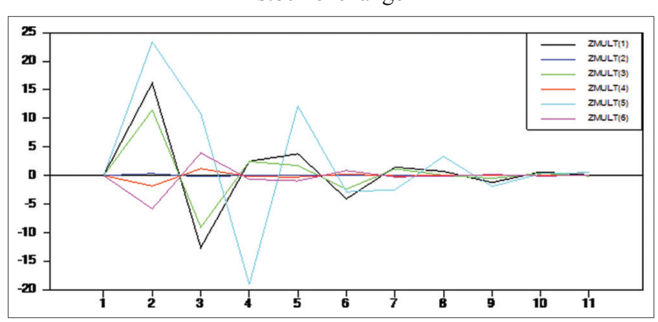
Data source: World Health Organization. (2022). COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. GitHub. https://github.com/CSSEGISandData/COVID-19. Accessed on January 24, 2023. Athens Stock Exchange. Accessed on January 24, 2023. https://www.athexgroup.gr/index-historic

Figure 2: The dynamic effects of the number of COVID-19 intensive care units on the Athens stock exchange



Data source: World Health Organization. (2022). COVID-19 Data repository by the center for systems science and engineering (CSSE) at Johns Hopkins University. GitHub. https://github.com/CSSEGISandData/COVID-19. Accessed on January 24, 2023. Athens Stock Exchange. Accessed on January 24, 2023. https://www.athexgroup.gr/index-historic

Figure 3: The dynamic effects of COVID-19 deaths on the Athens stock exchange



Data source: World Health Organization. (2022). COVID-19 data repository by the center for systems science and engineering (CSSE) at Johns Hopkins university. GitHub. https://github.com/CSSEGISandData/COVID-19. Accessed on January 24, 2023. Athens Stock Exchange. Accessed on January 24, 2023. https://www.athexgroup.gr/index-historic

travel, hospitality, and retail, are particularly susceptible to case increases, influencing related stocks. Government responses to cases, including stimulus packages and regulatory changes, can also influence market movements. Positive news regarding vaccines can counteract negative case-related effects by boosting market confidence. Furthermore, the announcement of increased cases can lead to higher market volatility as traders react to the prevailing uncertainty. This intricate interplay reflects how health, economic factors, and investor sentiment collectively shape the stock market in the ongoing pandemic context. Figure 2 depicts the dynamic effects of the number of COVID-19 ICUs on the ASE.

The number of COVID-19 intensive care units (ICUs) plays a pivotal role in shaping stock market indices, and this interplay is characterized by its intricate nature. Firstly, there exists a profound correlation between health and the economy; a surge in ICU numbers is often indicative of a spike in severe COVID-19 cases, which, in turn, triggers concerns regarding the strain on the healthcare system and the potential for economic disruptions. This triggers reactions from investors who are closely attuned to these concerns. Secondly, government responses to ICU capacity, such as implementing lockdowns or restrictions, can have sector-specific impacts, exerting influence on distinct segments of the stock market. Thirdly, developments on the vaccine and treatment front have the potential to offset negative ICU-related effects, instilling confidence in investors. Lastly, the psychological aspect is significant, as ICU data acts as a tangible indicator of the pandemic's severity, affecting investor sentiment. In summation, ICU numbers, as a critical health metric, are intrinsically entwined with broader economic and psychological factors, contributing to the complexity of their influence on the stock market. Figure 3 presents the dynamic effects of COVID-19 deaths on the ASE.

The dynamics between the number of COVID-19 deaths and the stock market index are intricate and multifaceted. Firstly, the rise in COVID-19 fatalities can significantly impact economic sentiment. Investors closely monitor death tolls as they serve as indicators of the pandemic's severity and its potential to disrupt the economy, often leading to market downturns. Secondly, government responses to escalating death tolls are critical. Measures such as lockdowns and travel restrictions implemented in response to higher death counts can have sector-specific effects, influencing distinct segments of the stock market. Thirdly, the trajectory of vaccine and treatment developments is vital. Positive news regarding vaccines or treatments can offset the negative impacts of rising deaths, bolstering investor confidence. Lastly, the global dimension is noteworthy. COVID-19 deaths on a global scale can influence international market sentiment, especially for companies with global operations. In summary, the number of COVID-19 deaths wields substantial influence over the stock market. Investors carefully track health data in conjunction with economic and political developments to navigate this multifaceted relationship.

2.2. Unit Root (Stationarity) Test

The Augmented Dickey-Fuller (ADF, 1979) test is a widely used method for examining the presence of unit roots in time series models. The results of the ADF test, based on equations (1) and (2), indicate that all variables under investigation are not stationary in their original form but exhibit integrated order one, I(1), when examined in their first differences. These two standard regression equations are employed for conducting the ADF unit root test within the context of an autoregressive (AR) process.

$$\Delta Y_t = \alpha + \lambda Y_{t-1} + \sum_{i=1}^{P} \beta_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta Y_t = \alpha + \delta t + \lambda Y_{t-1} + \sum_{i=1}^{P} \beta_i \Delta Y_{t-i} + \varepsilon_t \quad (2)$$

where Δ represents the first difference operator, and parameters α, λ, β, t (time trend), and α (constant) are estimated. The error term (ε_t) is characterized as a white noise disturbance term, and the ΔY_{t-i} term accommodates autocorrelation while ensuring the ε_t term remains white noise. The null hypothesis, denoting the presence of a unit root in Y_t, is H_0 for equation 1 (equation 2), indicating that λ=0, α=0 (λ=0, δ=0). The critical value for each ADF equation is unique and determined by the size of the sample.

Table 1a presents the ADF test results for various lags, providing insights into the stability of the variables. It shows that no ADF test results on the original series are statistically significant. It also indicates that as the number of lags increased, the ADF test statistic became less negative for all the three (CASES, DD, and METH) series. This trend suggests an improvement in stationarity with additional lags. The enhanced stationarity of the variables is an important consideration in time series analysis, as it ensures reliable forecasting and modeling capabilities.

To further analyze stationarity, the first differences in the time series were considered. Table 1b presents the ADF test results for the first differences, providing additional insights into the stability of the variables. The results for the first differences of the series demonstrated stationarity across all variables. In the case of ΔCASES, all ADF test statistics remained negative across different lags, providing evidence against the null hypothesis of non-stationarity. Similarly, the ADF test statistics for ΔDD and ΔMETH were negative, indicating stationarity in the first differences. These findings suggest that the variables exhibit stability in their first-differenced form, further supporting the reliability of the data for analysis.

Table 1a: The ADF Unit Root Test testing stationarity (test of the original series)

Variable	ADF (0)	ADF (1)	ADF (2)	ADF (3)	ADF (4)
CASES	−2.320	−2.926	−1.973	−2.128	−1.699
GCLOSE	−1.217	−6.213*	−1.810	−1.660	−1.373
RAT	−3.229	−6.213*	−0.047	−4.407*	−3.916**
RATE	−2.279	−3.490**	−2.940	−3.105	−2.652

Critical table values for 1% and 5% are−4.11 and−3.48, (Mackinnon, 1991). *, ** denote rejection of the null hypothesis of unit root at 1% and 5%, respectively

Table 1b: The ADF unit root test (test of the first differences)

Variable	ADF (0)	ADF (1)	ADF (2)	ADF (3)	ADF (4)
ΔCASES	−12.581*	−6.715*	−6.298*	6.854*	−5.341*
ΔGCLOSE	−8.018*	−6.715*	6.298*	−6.854*	−5.341*
ΔRAT	−9.868*	−7.066*	−6.258*	−6.665*	−6.022*
ΔRATE	−8.787*	−7.283*	−6.166*	−5.269*	−4.828*

Critical table values for 1% and 5% are−3.54 and−2.91, (Mackinnon, 1991). * denote rejection of the null hypothesis of unit root at 1%

In summary, the absolute ADF statistic of the level data is smaller than the critical values specified in Table 1a and b. Consequently, the variables in their original levels exhibit non-stationarity, indicating the presence of a unit root. However, the results of the ADF unit root test reveal a different story for the data in the first difference form. In this case, the t-values surpass the critical values, leading us to reject the null hypothesis. This implies that all the variables have become integrated into order one, denoted as [I(1)]. Given that all four series in their first difference form are stationary and have no unit roots, it becomes necessary to proceed with a pairwise Granger causality test on this transformed data.

2.3. Granger Causality

Granger causality (GC) has been a widely used concept in economics since the 1960s. Granger proposed a method for testing causality by analyzing how each variable in a model relates to its past values and those of other variables, as described in equations (3) and (4) (Granger, 1969). There are several approaches to implementing GC tests. In our research, we employed a bivariate linear autoregressive model involving two variables, Y and X.

$$Y_t = \varphi_0 + \sum_{i=1}^{P} \delta_i Y_{t-i} + \sum_{j=1}^{P} a_i X_{t-j} + u_{1t} \quad (3)$$

$$X_t = \gamma_0 + \sum_{i=1}^{q} \chi_i X_{t-i} + \sum_{j=1}^{q} \beta_i Y_{t-j} + u_{2t} \quad (4)$$

where p and q represent the maximum number of lagged observations included in the model, and u_1 and u_2 denote the residuals for each time series. If the variance of u_1 (or u_2) decreases due to the inclusion of the Y (or X) terms in equation 3 (or 4), it indicates that X (or Y) Granger causes Y (or X). This concept is rooted in GC, a statistical hypothesis test used to evaluate causal relationships between time series data.

Based on the estimated ordinary least squares (OLS) coefficients for equations (1) and (2), four different alternative hypotheses (H_1) are formulated: (i) $\alpha_j \neq 0$, $\beta_j = 0$ (j=1, 2,…, n) indicates causality running from X to Y, implying that X enhances Y's prediction, but not vice versa; (ii) $\beta_j \neq 0$, $\alpha_j = 0$ (j=1, 2,…, n) suggests causality from Y to X; (iii) $\alpha_j \neq 0$ and $\beta_j \neq 0$, indicating bidirectional GC from X to Y and vice versa; (iv) $\alpha_j = 0$ and $\beta_j = 0$, implying no causality between Y and X.

The GC test's effectiveness is influenced by the number of lags. Researchers determine the optimal lag length, denoted as k, to ensure the estimated model is free from autocorrelation and heteroscedasticity, often employing tests like the Lagrange Multiplier test (LM) and Breusch-Pagan-Godfrey test (BPG). The results of the GC test for equations (3) and (4) are presented in Table 2, where the H_0 hypothesis, representing the absence of causality, is tested along a row.

The table displays the outcomes of a GC test involving different models with variables Y, X_1, X_2, and X_3. Model 1 indicates a significant causality at the 1% level, revealing that past values of X1 can predict Y. Model 4 and Model 5 both exhibit significant causality at the 10% level, with Y(4) predicting X3(4) and X2(4) predicting Y(4), respectively. Meanwhile, Models 2, 3, and 6 demonstrate no significant causality between their respective variables. The LM and BPG P-values further support these findings. This suggests that there is evidence of GC in some relationships, specifically involving X_1, Y, X_2, and X_3, highlighting the predictive influence of past values on certain variables in the given models. In summary, the significant P-values in Models 1, 4, and 5 suggest GC, indicating that there is evidence to support the idea that past values of certain variables can predict future values of others.

2.4. Hsiao's Granger Causality Test (or Stepwise Granger Causality)

Hsiao (1981) modified the GC test aimed at addressing the challenge of selecting the appropriate lag length, a limitation encountered in Granger's original method. Instead of relying on the F-test, Hsiao employed the final prediction error (FPE) criteria to determine causality. This criterion was used to identify the optimal lag length for the stationary variables X and Y. In the first step of Hsiao's approach, the controlled variable Y is regressed against

Table 2: The results of granger causality test

No	Model	F statistic (P-value)	Causality	LM P value	BPG P value
1	*Y=f(Y (1), X1 (1))*	10.344 (0.000)*	+ *X1 (1) →Y (1)* [0.076]*	0.556	0.316
2	*X1=f(X1 (1), Y (1))*	0.223 (0.756)	No	0.143	0.789
3	*Y=f(Y (4), X3 (4))*	0.289 (0.946)	No	0.578	0.602
4	*X3=f(X3 (4), Y (4))*	2.246 (0.088)***	+ *Y (4)→ X3 (4)* [2.672]	0.211	0.310
5	*Y=f(Y (4), X2 (4))*	2.267 (0.079)***	*X2 (4) →Y (4)* [0.122]**	0.801	0.598
6	*X2=f(X2 (4), Y (4))*	0.613 (0.623)	No	0.358	0.699

*, **, and *** denote significant 1, 5, and 10% levels

Table 3: Hsiao's granger causality test

No	Model (lags)	F statistic (P-value)	FPE 1	FPE 2	Causality
1	*Y=f(Y (1), X1 (1))*	10.678 (0.001)*	2.899	2.545	+ *X1 (1) →Y (1)* [0.072]*
2	*X1=f(X1 (1), Y (1))*	0.192 (0.756)	0.00782	0.00902	No
3	*Y=f(Y (4), X3 (4))*	0.284 (0.928)	2.989	3.186	No
4	*X3=f(X3 (4), Y (4))*	3.098 (0.082)***	0.00397	0.00367	+ *Y (4)→ (X3 (4)* [2.505]
5	*Y=f(Y (4), X2 (4))*	4.136 (0.084)***	3.001	2.838	*X2 (4) →Y (4)* [0.139]**
6	*X2=f(X2 (4), Y (4))*	0.901 (0.598)	0.00733	0.00756	No

*, **, and *** denote significant 1, 5, and 10% levels. Decimal numbers in the brackets are the sum of the lag coefficients of independent causal variables

its lags ranging from 1 to m, as represented in equation (5). The optimal lag length, m, is established by identifying the point at which the FPE is minimized. This is determined using equation (6), which considers T as the number of observations, SSE as the sum of squared residuals, and m as the lag length that generates the lowest FPE.

$$Y_t = a + \sum_{i=1}^{m} \beta_i Y_{t-i} + \varepsilon_{1t} \quad (5)$$

$$FPE(m,0) = ((T+m+1)/(T-m-1))(SSE(m,0))/T \quad (6)$$

After a lag length of Y in equation (5) is determined, the second stage requires including the manipulated variable X on its lags from 1 to n in equation (7), then computing the minimum FPE (m, n) value in the formula (8) as follows:

$$Y_t = a + \sum_{i=1}^{m} \beta_i Y_{t-i} + \sum_{j=1}^{n} \Phi_j X_{t-j} + \varepsilon_{2t} \quad (7)$$

$$FPE(m,N) = ((T+m++N+1)/(T-m--n-1))(ESS(m,n))/T \quad (8)$$

In the final stage, If FPE (m)>FPE (m, n), then we accept the hypothesis that X causes Y. On the contrary, if FPE (m) <FPE (m, n), we cannot reject the null hypothesis, no causality from X to Y. If FPE (m, n) <FPE (m) in both equations, then we conclude that there is a bidirectional causality between Y and X. For the reverse causation from X to Y also be estimated by repeating the same stages by repeating stage (1) to (2) with X as the controlled and Y as manipulated variable.

Table 3 presents the results of Hsiao's GC test for different models involving variables Y, X_1, X_2, and X_3, considering different lags.

In Model 1, there is significant GC at the 1% level, suggesting that past values of X1 can predict Y. However, Model 2 shows no significant causality between X1 and Y. Similarly, Models 3 and 6 reveal no significant GC between Y and X3, and X2, respectively. Model 4 and Model 5, on the other hand, indicate significant causality at the 10% level, with Y(4) predicting X3(4) and X2(4) predicting Y(4), respectively. The FPE values provide additional insight, and the lag coefficients in brackets indicate the sum of lag coefficients of independent causal variables. Overall, Hsiao's GC test suggests varying degrees of predictive relationships among the studied variables, with some models showing significant causality at different confidence levels.

3. CONCLUSION

The COVID-19 pandemic has had a profound impact on the Greek stock market, paralleling trends observed in other global financial markets. The findings of this study indicate that pandemic-related variables, such as lockdown measures and mobility restrictions, significantly negatively affected the Athens stock exchange (ASE). These restrictions disrupted economic activities, leading to decreased investor confidence and market volatility. On the other hand, it also highlights the positive influence of interest rates on the ASE. The reduction in interest rates aimed at stimulating economic growth provided a boost to the stock market by lowering the cost of borrowing and encouraging investment. This effect underscores the critical role of monetary policy in stabilizing financial markets during times of crisis. Overall, the dual impacts of pandemic-induced restrictions and monetary policy adjustments illustrate the complexity of market dynamics during unprecedented events like COVID-19. Policymakers and investors must consider these multifaceted influences when making decisions to handle future economic uncertainties effectively.

The fundamental limitation of this study is that it is restricted to the context of Greek culture. It would be beneficial to broaden the scope of the research to include additional European countries that have been affected by the COVID-19 pandemic and to compare the responses of each. In addition, several country counts, in addition to other statistical or economic methods, could be used (e.g., dynamic panel modeling). Only new cases and new deaths attributable to coronavirus were included as pandemic variables in this analysis.

More research is needed to fully understand how the COVID-19 pandemic may affect the financial market and other facets of society. Fewer studies have looked at nations that were badly hit by the COVID-19 epidemic, while most have looked at groups of countries (such as East Asian countries or countries in the West African Economic and Monetary Union) (e.g., China, USA, UK, Italy).

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