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(4), 214-221.

The Impact of COVID-19 on the Cypriot Stock Market Dynamics

Christos Christodoulou-Volos*, Dikaios Tserkezos

Department of Economics and Business, Neapolis University Pafos, Cyprus. *Email: c.volos@nup.ac.cy

Received: 15 January 2024 **Accepted:** 30 May 2024 **DOI:** https://doi.org/10.32479/ijefi.15875

ABSTRACT

This paper examines the effects of coronavirus disease 2019 (COVID-19) pandemic outbreak on the cypriot stock exchange (CSE), which has encountered substantial turmoil. For this purpose, daily stock market returns were used over the period of September 3, 2019-July 10, 2020, for the Cypriot economy. The study applied Granger causality models to explore whether the CSE is impacted by the crisis generated by novel coronavirus. Hsiao's approach to Granger causality was employed to investigate the causalities among COVID-19 and stock market returns, as well as between pandemic measures and several commodities. The analyses uncover intricate dynamics and contributing factors, shedding light on the observed volatility. The findings demonstrate significant volatility throughout the pandemic, with notable shifts in market conditions. Nevertheless, the stock market showcased resilience and recovery during the initial shutdown period. These insights contribute to understanding the pandemic's impact on the CSE, offering crucial guidance for investors, policymakers, and market participants.

Keywords: Coronavirus Disease 2019, Unit-root Test, Stock Market, Hsiao's Approach, Granger Causality
JEL Classifications: C32, E44, G14, G17

1. INTRODUCTION

Research on the consequences of the COVID-19 pandemic has gained significant momentum since the World Health Organization (WHO) declared it a global epidemic in March 2020. The outbreak has had a detrimental effect on financial markets, increasing the level of global financial risk (Al-Awadhi et al., 2020; Baker et al., 2020). Empirical studies have shown that market returns have decreased dramatically during this period due to the growing uncertainty induced by the global epidemic, which has been caused by the spread of the pandemic (Al-Awadhi et al., 2020).

The dramatic drop in stock prices that has been observed across all of the world's stock markets. When compared to its all-time high on February 18, 2020, the S&P 500 Index had a drop on March 23, 2020, that was 35% more than the typical decline. This drop came after the index reached its all-time high on February 18, 2020. This historic fall, which took place over a short period of time, had an intensity that was equivalent to that of the financial crisis that took place in 2008, black Monday, which took place in 1987, and the great depression, which took place in October and November of 1929 (Helppie McFall, 2011).

In March of that year, the S&P 500 index in the United States had a drop of 30%, as stated by Fernandes (2020). He then went on to say that the stock markets in Germany and the United Kingdom had both performed noticeably worse than the market in the United States. These two markets saw a decline in returns on investment of 37% and 33%, respectively, over that period. When compared to the performance of other major stock markets throughout the world, Brazil and Columbia's stock markets had the worst performance. Brazil's loss was 48%, and Columbia's loss was 47%.

The Nikkei 225 index in Japan witnessed a loss of more than 20% when compared to its all-time high, which was attained in December of 2019. The Dow Jones Industrial Average and the S&P 500 both had a fall of 20% during the month of March in the year 2020. The Nikkei Index was also brought down as a direct consequence of the slump in the economy.

The Colombo Stock Exchange was able to rebound, but not before it suffered a 9% decrease in share value and experienced three trading halts in the middle of March 2020. Eventually, the CSE was successful in regaining its footing. After this, the stock market in Indonesia experienced a downturn like the rest of the markets around the world. The previous value of the index was lower when the month of April 2020 began, which resulted in a fall of 64.06 points in the index. A loss of 29.72% was experienced by the FTSE index in the UK. The value of the DAX (Germany) fell by 33.37%, the value of the CAC (France) fell by 33.63%, the value of the NIKKEI (Japan) fell by 26.85%, and the value of the SUNSEX (India) fell by 17.74%.

On March 23, 2020, the Shanghai composite index hit a new all-time low of 2,660.17, reflecting a fall of 12.49% from its new all-time high, which was established in December 2019. On December 27, 2019, the KOSPI hit its all-time high of 2,204.21 points, and on March 19, 2020, it reached its all-time low of 1,457.64 points, which represents a decline of 33.87%. On December 20, 2019, the BSE SENSEX reached an all-time high of 41,681.54 points, which was the index's new record. On March 23, 2020, the BSE SENSEX reached a new all-time low of 25,981 points as a direct result of the pandemic caused by COVID-19. A decrease of 37.54% was witnessed in the S&P/ASX 200 index in Australia, and the KOSPI index in South Korea experienced a loss of 19.94%.

Overall, the stock market downturn in 2020 caused by the COVID-19 pandemic had a significant impact on global stock markets, resulting in substantial declines in many major indices worldwide. The extent of the decline varied across countries, but the overall trend was a significant drop in stock prices and market values.

Ozili and Arun (2020) conducted an empirical study on the policy of social distance that was put into place to limit the spread of the Coronavirus across all four continents. The results of their study indicate that a strategy of social isolation or lockdown that is carried out for a period of 30 days has a detrimental effect, both on the value of stocks and on the economy. Azimili (2020), using quantile regression, investigated how the coronavirus altered the level of risk-return dependency in the United States and how it was organized. The findings indicate that the COVID-19 epidemic caused an increase in the degree of dependency between returns and market portfolios in the upper quantiles. He also investigated the connection between Granger Causality and the returns on stock investments, and he discovered an unbalanced pattern in which the lower tails of the distribution were impacted negatively approximately twice as much as the upper tails. Shehzad et al. (2020) utilized the asymmetric power granger model in order to carry out an analysis of the nonlinear behavior of the financial markets of the United States of America, Italy, Japan, and China. This analysis was conducted in order to compare and contrast the nonlinear behaviors of these markets. The results of the investigation showed that COVID-19 had a negative impact on the returns that were generated by the stocks that are included in the S&P 500. After conducting a more in-depth analysis, it was found that the influence had a negligible effect on the Nasdaq Composite index. Cepoi (2020) undertook an empirical study with the purpose of evaluating whether the transmission of information regarding COVID-19 had an influence on the stock market results in the countries that were most negatively affected by the disaster, using panel quantile regression. He concluded that the dependence of the stock market on news regarding COVID-19 was not uniform. Osagie et al. (2020) applied quadratic granger and exponential granger models using dummy variables to determine that COVID-19 reduces stock returns in Nigeria. To enhance the functioning of the country's financial market, the authors advocated for the establishment of a politically secure environment, the provision of an incentive to domestic businesses, the diversification of the economy, and a flexible exchange rate regime.

Ravi (2020) researched the Indian stock market before and after the COVID-19 and he discovered that the NSE and BSE trade reached their respective all-time highs immediately prior to COVID-19, with the NSE reaching 12,362 and the BSE reaching 42,273, respectively. After the COVID-19 outbreak, tensions were high in the stock markets since both the BSE Sensex and the NSE Nifty experienced losses of 38%. Because of this, the overall value of the stock market has declined by 27.31% since the beginning of the year. The stock of other enterprises, such as the hotel, tourist, and entertainment industries, has decreased by more than 40% as a direct result of the limits placed on transportation (Vishnoi and Mookerjee, 2020). Mandal has carried out a comprehensive examination of the manner in which the devastating effects of the virus have been having an impact on the stock market in India (2020). The data show that the 1-day decrease in the BSE Sensex of 13.2% was bigger than the drop of 10% that took place on 7 August 2007 (Mandal, 2020). After the initial scare, the Sensex returned to normal.

According to Vishnoi and Mookerjee's (2020) calculations, the value of the Japanese stock market experienced a decline of almost 20% in the month of December 2019. The value of equities in Spain, Hong Kong, and China all decreased during March 8-18, 2020, by a total of 25.1%, 14.75%, and 12.1%, respectively. This was the most recent available data (Shehzad et al., 2020). Their (2020) investigation found that there was a negative influence on the returns of stocks in the S&P 500 index, although there was no discernible effect on the Nasdaq Composite. Georgieva (2020) claims that the globe came perilously near to experiencing a financial collapse that was much more catastrophic than the global crises that occurred in 2007 and 2008.

To investigate the relationship between COVID-19 variables and CSE General Index, the study employed the Granger causality test (Granger, 1969), a statistical tool used to determine the direction of causality between variables. By analysing the time series of stock performance and COVID-19 sub-variables, the study aims to identify whether incorporating information from one series improves the prediction of the other. The analysis considered various COVID-19 sub-variables, including COVID-related deaths, hospitalizations, ICU admissions, and daily reported new cases, in relation to the stock performance.

The rest of this paper is structured as follows. Section 2 presents data, 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 from GitHub and the Cyprus Stock Exchange (CSE) General Index, respectively, covering the period from March 9, 2020 (the first two confirmed cases of COVID-19 in Cyprus) to January 23, 2023. 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 daily deaths (DD), intensive care (ICU) admissions due to *COVID*-19 (METH), and daily reported new cases (Cases). The closing daily stock prices were utilized for the study.

2.1. COVID-19 Data

In the wake of the global COVID-19 pandemic, understanding the relationship between public health factors and financial markets has become crucial. While the pandemic has had significant impacts on economies worldwide, studying the local dynamics of stock performance provides valuable insights for investors, policymakers, and the public. By examining the relationship between COVID-19 variables and stock performance in the CSE General Index, this analysis contributes to our understanding of the interplay between public health and the financial markets.

The co-variability analysis, as depicted in Figures 1-4, has revealed a strong and dependable relationship between the CSE General Index and the various sub-variables associated with COVID-19. This significant discovery implies that alterations in the metrics related to COVID-19 are highly likely to exert a noticeable influence on the overall performance of stocks within the CSE General Index. In simpler terms, these findings suggest that as COVID-19-related factors change, they can have a measurable impact on how the CSE General Index behaves, potentially affecting the stock market in a discernible manner. This connection underscores the interconnectedness of public health factors, such as the spread of the virus, and the financial markets, highlighting the importance of monitoring and understanding these dynamics in the context of investment and economic decision-making.

Further examination of the co-variability analysis showed interesting behaviours in the combinations of certain variables. For instance, the cases and DD time series, as well as the METH and DD time series, exhibited "broken" time series with jumps at various points. In contrast, the METH and cases combination yielded a continuous time series. These observations shed light on the nuanced relationship between COVID-19 variables and stock performance, indicating that certain combinations of variables may have distinct impacts on market dynamics.

2.2. Unit Root (Stationarity) Test

The Augmented Dickey and 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.

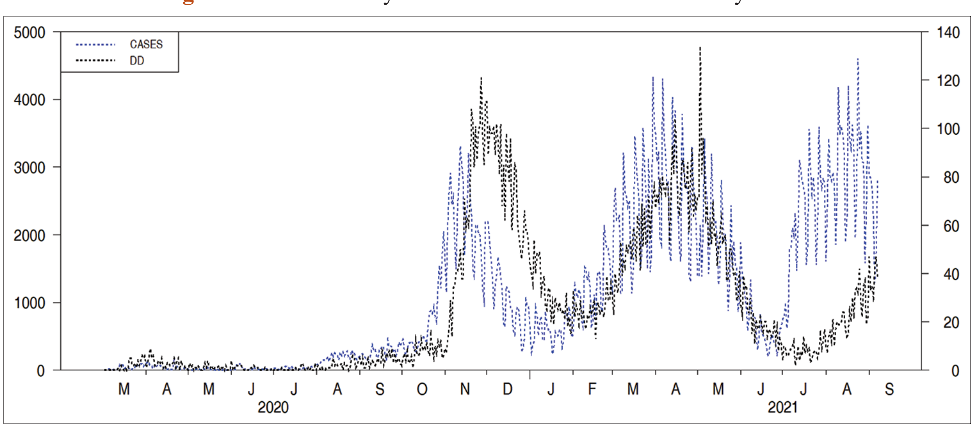
$$\Delta Y_t = \alpha + \lambda Y_{t-1} + \sum_{i=1}^{P} \beta_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

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

Where Δ represents the first difference operator, and parameters α, λ, β, t (time trend), and α (constant) are estimated. The error term (εt) is characterized as a white noise disturbance term, and the ΔYt-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 $\lambda = 0$, $\alpha = 0$ ($\lambda = 0$, $\delta = 0$). The critical value for each ADF equation is unique and determined by the size of the sample.

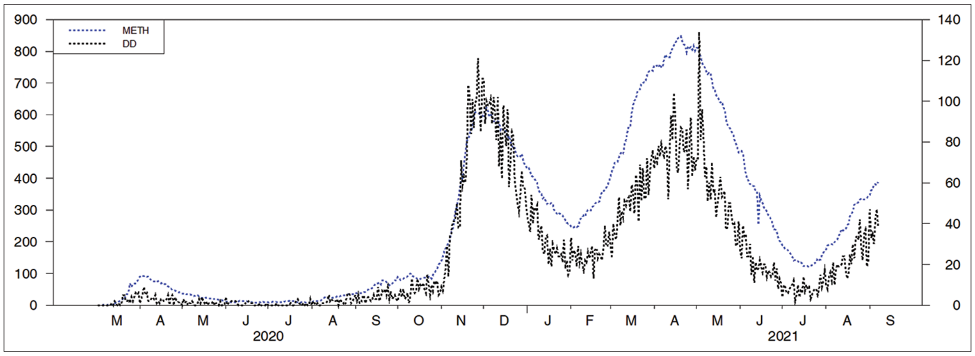
Table 1a presents the ADF test results for various lags, providing insights into the stability of the variables. It shows that no ADF

Figure 1: Co-variability between COVID-19 cases and daily deaths



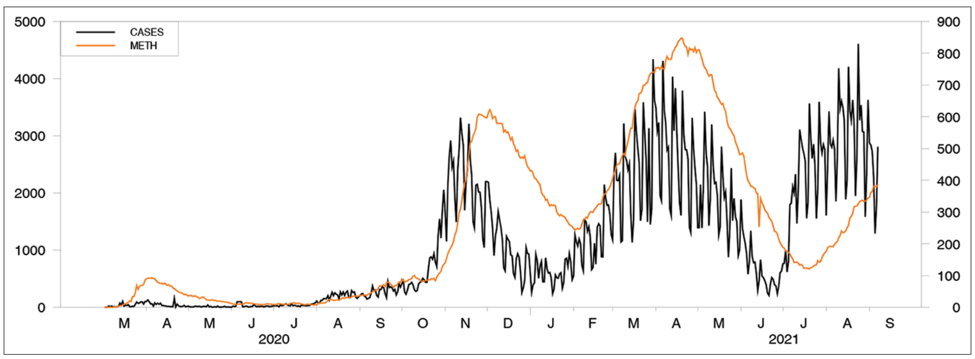
Data source: World Health Organization. (2022). COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. GitHub. https://github.com/CSSEGISandData/COVID-19. Accessed on January 24, 2023

Figure 2: Co-variability between daily deaths and ICU Admissions (METH)



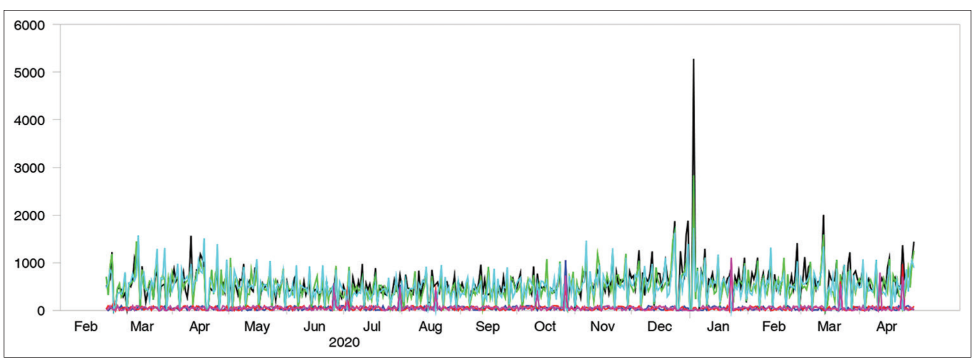
Data source: World Health Organization. (2022). COVID-19 data repository by the center for systems science and engineering (CSSE) at Johns Hopkins University. GitHub. https://github.com/owid/covid-19-data/tree/master/public/data. Accessed on January 24, 2023

Figure 3: Co-variability between COVID-19 Cases (CASES) and ICU Admissions (METH)



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/owid/covid-19-data/tree/master/public/data. Accessed on January 24, 2023

Figure 4: Co-variability of COVID-19-Related Variables (DD, CASES, METH) with the CSE general index



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/owid/covid-19-data/tree/master/public/data. Accessed on January 24, 2023. CSE Official Web Site. https://www.cse.com.cy/en-GB/home/. Accessed on January 12, 2023

test results on the original series is statistically significant. It also indicates that as the number of lags increased, the ADF test statistic became less negative for all the three (CASES [X_1], DD [X_2], and METH [X_3]) 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 modelling capabilities.

To further analyse stationarity, the first differences of 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 DCASES, all ADF test statistics remained negative across different lags, providing evidence against the null hypothesis of non-stationarity. Similarly, the ADF test statistics for DDD and DMETH 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.

In summary, the absolute ADF statistic of the level data is smaller than the critical values specified in Tables 1a and b. Consequently,

Table 1a: The ADF unit root test (test of the original series)

Variables	ADF (0)	ADF (1)	ADF (2)	ADF (3)	ADF (4)
CASES	−1.56	−1.69	−0.62	−0.53	−0.52
DD	−1.95	−2.68	−1.34	−1.38	−1.31
METH	−1.57	−2.22	−1.10	−1.52	−1.37

Critical table values for 1% and 5% are−4.11 and−3.48, (Mackinnon, 1991).
ADF: Augmented Dickey and Fuller

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

Variables	ADF (0)	ADF (1)	ADF (2)	ADF (3)	ADF (4)
ΔCASES	−4.06*	−5.95*	−5.04*	−3.59*	−2.00
ΔDD	−3.22**	−5.72*	−2.97**	−2.23	−1.01
ΔMETH	−2.85	−5.57*	−1.99	−1.42	−0.54

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%, 5%, respectively. ADF: Augmented Dickey and Fuller

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 its 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 of order one, denoted as (I[1]). Given that all three 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 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 own past values and those of other variables, as described in equations (3) and (4) (Granger, 1969, pp. 424-438). There are several approaches to implement Granger causality tests. In our research, we employed a bivariate linear autoregressive model involving two variables, Y_t and X_t.

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

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

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_t (or X_t) terms in equation 3 (or 4), it indicates that X_t (or Y_t) Granger causes Y_t (or X_t). This concept is rooted in Granger causality, 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_t to Y_t, 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_t to X_t.
iii. $\alpha_j \neq 0$ and $\beta_j \neq 0$, indicating bidirectional Granger causality from X to Y and vice versa.
iv. $\alpha_j = 0$ and $\beta_j = 0$, implying no causality between Y_t and X_t.

The Granger causality 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 Granger causality 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 results of Granger's Causality test are summarized across six models. In Model 1 ($Y = f[Y(1), X_1(1)]$), the F statistic is 10.129 with a P = 0.001, indicating statistical significance at the 1% level. Causality is observed, with X1(1) → Y(1) being significant at the 1% level, suggesting that X_1 Granger causes Y with a lag of 1. The LM P = 0.524, and the BPG P = 0.322. Conversely, in Model 2 ($X_1 = f[X_1(1), Y(1)]$), the F statistic is 0.217 with a P = 0.643, indicating no statistical significance. There is no evidence of Granger causality between X_1 and Y(1) at any significance level, and the LM P = 0.123, with a BPG P = 0.774. Models 3, 4, 5, and 6 also provide insights into the absence or presence of Granger causality between the variables, highlighting significant relationships at the 10% level in Models 4 and 5. The LM and BPG P-values across the models offer additional robustness checks for the Granger causality findings. The Wald F test results reveal that the cumulative lag coefficients of independent causal variables leading to a causal effect in models 1, 4, and 5 are 0.079 for X_1, 2.576 for Y, and 0.139 for X_2, indicating positive causality at the 1%, 1%, and 5% significance levels in all three equations, respectively.

In summary, Table 2 provides a thorough perspective on the notable causal connections and related statistical metrics within each model. This offers valuable insights into the temporal dynamics and potential interdependencies among the variables being examined.

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

Hsiao (1981) introduced a modification of the Granger causality 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 its own 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.

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

Table 2: The results of granger causality test

S. No.	Model	F statistic (P-value)	Causality	LM P value	BPG P value
1	$Y=f(Y[1], X1[1])$	10.129 (0.001)*	$+X_1(1) \rightarrow Y(1)$ [0.079]*	0.524	0.322
2	$X_1=f(X_1[1], Y[1]))$	0.217 (0.643)	No	0.123	0.774
3	$Y=f(Y[4], X_3[4])$	0.255 (0.901)	No	0.568	0.581
4	$X_3=f(X_3[4], Y[4])$	2.103 (0.091)***	$+Y(4)\rightarrow X_3(4)$ [2.576]	0.223	0.302
5	$Y=f(Y[4], X_2[4])$	2.244 (0.084)***	$X_2(4) \rightarrow Y(4)$ [0.139]**	0.751	0.604
6	$X_2=f(X_2[4], Y[4])$	0.723 (0.584)	No	0.342	0.713

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

Table 3: Hsiao's Granger causality test

S. No	Model (lags)	F statistic (P-value)	FPE 1	FPE 2	Causality
1	$Y=f(Y[1], X1[1])$	10.456 (0.000)*	2.994	2.556	$+X_1(1) \rightarrow Y(1)$ [0.067]*
2	$X_1=f(X_1[1], Y[1])$	0.189 (0.733)	0.00812	0.00884	No
3	$Y=f(Y[4], X_3[4])$	0.263 (0.914)	2.997	3.172	No
4	$X_3=f(X_3[4], Y[4])$	3.103 (0.087)***	0.00411	0.00388	$+Y(4)\rightarrow (X_3(4)$ [2.469]
5	$Y=f(Y[4], X_2[4])$	4.122 (0.089)***	2.996	2.847	$X_2(4) \rightarrow Y(4)$ [0.142]**
6	$X_2=f(X_2[4], Y[4])$	0.839 (0.641)	0.00727	0.00769	No

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

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

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

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

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

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 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, (1) to (2), with X as the controlled and Y as manipulated variable.

Table 3 presents the results of Hsiao's Granger Causality Test, exploring causal relationships between variables in different models.

In Model 1 (Y = *f*[Y(1), X_1(1)]), the F statistic is 10.456 with a P = 0.000, indicating statistical significance at the 1% level. The model has a FPE of 2.994 and 2.556 for the first and second specifications, respectively. Causality is established, with $X_1(1) \rightarrow Y(1)$ being significant at the 1% level, suggesting that X_1 Granger causes Y with a lag of 1. Model 2 (X_1 = *f*[X_1(1), Y(1)]) shows a non-significant F statistic of 0.189 with a P = 0.7333, and there is no evidence of Granger causality between X_1 and Y(1). The FPE values for Model 2 are 0.00812 and 0.00884. Models 3 and 6 exhibit no statistical significance in the relationship between the variables. In contrast, Models 4 and 5 demonstrate significant Granger causality at the 10% level, providing valuable insights into the temporal dynamics and directional relationships between the variables in the specified lag contexts. The FPE values for Models 3, 4, 5, and 6 are 2.997, 0.00411, 2.996, and 0.00727, for the first specification and 3.172, 0.00388, 2.847, and 0.00769 for the second specification, respectively. The Wald F test results reveal that the cumulative lag coefficients of independent causal variables leading to a causal effect in models 1, 4, and 5 are 0.067 for X_1, 2.469 for Y, and 0.142 for X_2, indicating positive causality at the 1%, 1%, and 5% significance levels in all three equations, respectively. Overall, Table 3 offers a comprehensive view of the significant causal links and associated statistics between the variables in each model, providing insights into the temporal dynamics and potential dependencies among the variables under consideration.

In summary, Hsiao's Granger causality and standard Granger causality have reached the same conclusion. Additionally, by employing the lag length according to FPE criteria in Table 3, the null hypotheses are also tested by using the F-test. The F-test results listed in the second column of Table 2 have similar results with Hsiao's Granger causality.

3. CONCLUSION

The natural fluctuations in the value of financial assets are often driven by the dissemination of positive or negative information on a national or international scale. Regardless of the nature of the information, it has the potential to disrupt financial markets. While extensive research has been conducted on stock market returns and volatility in relation to various epidemics, definitive conclusions regarding the ongoing COVID-19 pandemic, which continues to unfold, have not yet been established.

Unlike previous epidemics that were confined to specific regions, the COVID-19 pandemic has impacted nearly every country worldwide. Consequently, investors are keenly interested in understanding the volatility induced by this health crisis in the stock market. Against this backdrop, the objective of this study was to analyse the impact of the ongoing COVID-19 pandemic on the return and volatility of stock market indices in Cyprus over the past two decades.

The study's findings reveal that the Cyprus Stock Exchange experienced the most significant negative cumulative abnormal returns and heightened volatility in response to the COVID-19 outbreak. This observation underscores the market's heightened sensitivity to the pandemic and suggests that it may not be an ideal location for portfolio diversification during times of crisis, particularly considering the ongoing COVID-19 pandemic. The economic conditions and growth of Cyprus's financial sector differed significantly from those of other countries, and the disruptive impact of the COVID-19 pandemic on the financial asset market further exacerbated the gap in economic growth.

In light of these conclusions, investors can capitalize on the inherent unpredictability of financial markets by rebalancing their investment portfolios to include assets perceived as carrying lower levels of risk. This strategic adjustment enables them to seize opportunities during periods of reduced risk.

To maintain stability and foster positive market sentiment, policymakers must adopt a proactive and ongoing strategy involving interventions in both fiscal and monetary policy. Only through such concerted efforts can policymakers achieve their objectives of preserving stability and positive sentiment in the market. In order to enhance participation in the capital market, the government should streamline regulations, encourage potential corporations to go public through initial public offerings (IPOs), and promote transparency in the financial industry. These measures will attract both domestic and foreign investors to the CSE.

The empirical findings from the Granger causality test indicate a significant relationship between the CSE General Index and COVID-19 variables. The COVID-19 variables, including the number of reported cases, ICU admissions, and COVID-related mortality, were identified as good predictors of the stock performance series. The F-test statistic values further supported the notion that X_t Granger-causes Y_t, while Y_t does not cause X_t. This implies that past values of COVID-19 variables contribute to the prediction of stock performance, highlighting their influence on the portfolio performance of the CSE General Index.

The implications of these findings extend to investors and policymakers alike. For investors, the significant relationship between COVID-19 variables and stock performance suggests the importance of closely monitoring and understanding the impact of the pandemic on the economy. Armed with this knowledge, investors can adjust their portfolios and develop strategies that consider the influence of COVID-19 on the CSE General Index. The findings provide valuable insights for investment decision-making and risk management, allowing investors to make more informed choices in a rapidly changing environment. Policymakers can also benefit from these findings. Understanding the causal relationships between COVID-19 variables and stock performance enables policymakers to make more informed decisions regarding public health measures and their potential impact on the economy. By considering the broader implications of these measures, policymakers can develop targeted policies and interventions that mitigate the negative effects of the pandemic on the financial markets. The findings emphasize the importance of balancing public health objectives with economic considerations and highlight the need for coordinated responses to ensure stability and resilience in the face of crises.

Although this empirical study provides valuable insights, it also faces several limitations that should be taken into account when interpreting its findings. Firstly, it acknowledges the ongoing nature of the COVID-19 pandemic, making it challenging to draw definitive conclusions as the situation continues to evolve. Additionally, the paper primarily focuses on the Cyprus Stock Exchange, and the generalizability of the findings to other financial markets may be limited. The unique economic conditions and growth patterns of Cyprus may contribute to variations not accounted for in the study. Moreover, the research relies on reported COVID-19 variables as predictors of stock performance, but it is essential to recognize that various external factors can influence financial markets and isolating the impact of COVID-19 alone may be complex. Furthermore, the study emphasizes the importance of rebalancing investment portfolios during periods of reduced risk, but individual investor preferences and risk tolerance levels may vary. Lastly, while the Granger causality test identifies significant relationships between COVID-19 variables and stock performance, it is crucial to note that correlation does not imply causation, and other unexplored factors may contribute to the observed associations. Despite these limitations, the paper provides valuable guidance for both investors and policymakers in navigating the complex interplay between the ongoing pandemic and financial markets, urging a cautious and adaptive approach.

REFERENCES

Al-Awadhi, A.M., Alsaifi, K., Al-Awadhi, A., Alhammadi, S. (2020), Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. Journal of Behavioral and Experimental Finance, 27, 100326.

Azimili, A. (2020), The impact of COVID-19 on the degree of dependence and structure of risk-return relationship: A quintile regression approach. Finance Research Letters, 36, 101648.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J., Sammon, M.C., Viratyosin, T. (2020), The Unprecedented Stock Market Impact of COVID-19. Working Paper No. 26945. Cambridge, England: NBER.

Cepoi, C.O. (2020), Asymmetric dependence between stock market returns and news during Covid-19 financial turmoil. Finance Research Letters, 36, 101658.

Dickey, D.A., Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.

Fernandes, N. (2020), Economic Effects of Coronavirus Outbreak (COVID-19) on the World Economy. IESE Business School Working Paper No. WP-1240-E.

Georgieva, K. (2020), IMF Managing Director Kristalina Georgieva's Statement Following a G20 Ministerial Call on the Coronavirus Emergency. United States: International Monetary Fund.

Granger, C.W.J. (1969), Investigating causal relations by econometric models and cross-spectral methods. Econometrica, 37(3), 424-438.

Helppie McFall, B. (2011), Crash and wait? The impact of the great recession on the retirement plans of older Americans. American Economic Review, 101, 40-44.

Hsiao, C. (1981), Autoregressive modeling and money-income causality detection. Journal of Monetary Economics, 7, 85-106.

MacKinnon, J. (1991). Critical Values for Cointegration Tests. In R. F. Engle & C. W. J. Granger (Eds.), Long-Run Economic Relationships: Readings in Cointegration (pp. 267-276). Oxford University Press.

Mandal, S. (2020), Impact of Covid-19 on Indian Stock Market. West Bengal: Adamas University.

Osagie, M., Maijamaa, A.B., John, D.O. (2020), On the Effect of COVID-19 Outbreak on the Nigerian Stock Exchange Performance: Evidence from GARCH Models [Preprints].

Ozili, P., Arun, T. (2020), Spillover of COVID-19: Impact on the Global Economy, MPRA Paper 99317. Germany: University Library of Munich.

Ravi, R. (2020), Impact of COVID-19 on Indian Stock Market, *Business* World. New Delhi, India: ABP Group. Available from: http://www.businessworld.in/article/impact-of-covid-19-on-the-indian-stock-markets/11-05-2020-191755

Shehzad, K., Xiaoxing, L., Kazouz, H. (2020), COVID-19's disaster is perilous than global financial crisis: A rumor or fact? Financial Research Letters, 36, 101669.

Vishnoi, A., Mookerjee, I. (2020), Perfect Storm Plunges Asia Stocks Bear Markets One by One. United Kingdom: Bloomberg.