Investigating the impact of the number of daily cases of the Coronavirus pandemic on the stock market indices of developed countries with the approaches of ARIMA and ARCH models

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Abstract

The scientific community still struggles to understand the magnitude of the worldwide infections and deaths induced by COVID-19, While policymakers have been able to eliminate its consequences by adopting and applying correct policies. In this paper, using the autoregressive integrated moving average (ARIMA) and autoregressive conditional heteroskedasticity (ARCH) methods, we quantify and show the impact of the COVID-19 spread in five countries, Japan, Australia, France, Britain, and the United States. Utilizing information criteria and forecasting accuracy measures, we show that the COVID-19 confirmed cases are statistically significant and contribute to the modeling of volatility.

Keywords: *COVID-19 pandemic, co-integration test, ARIMA method, ARCH method, stock markets*

1. Introduction

In 2019, a new public health crisis started threatening the globe. It started spreading in China and the new cases were identified in Wuhan city (Singhal, 2020). In early 2020, other cases started appearing in different European countries. And in March 2020 the World Health Organization (WHO) announced that COVID-19 is a pandemic. This widespread disease created disastrous hazards to people's socio-economic status. Apart from civil health, many economic sectors have been affected by the pandemic and the stock market is among the most vulnerable ones . Both negative and positive COVID-19 news could be impactful, although negative news seems to have been more impactful which suggests that the increase in the COVID-19 cases affects the stock market negatively in general (Kinross et al., 2020). investors showed signs of fear after observing the increase in the number of COVID-19 confirmed cases and their impulsive behavior led to unexpected nosedives in stock markets(Adekoya and Oliyide, 2021). Volatility is a practical approach of the dispersion of returns in most of the markets including the stock market. It is crucial for every investor to be aware of the impacts of a financial crises caused by disasters, COVID-19 for an instance, on the market's condition. As a result, governments around the world have been using a variety of methods to gauge and maintain the health of their economies (Hale et al., 2021). The aim of the project is to determine the effects of the pandemic and daily infected cases on volatility and return of the stock market in some countries which have major pairs of currencies, namely Japan, Australia, Britain and one chosen representative country from the Euro area which is France and also the United States(Juliet Orji et al., 2022). Every country felt the damages of the virus in a different way and their stock markets did not show the same response to the changes in the number of death and infected cases. In the US for example, job losses reached an unexampled high and unfortunately more than 10 million people have already lost their jobs (Li et al., 2023). VAR models suggest that the number of reported deaths in Italy and France have a negative impact on stock market returns. The CBOE Volatility Index (VIX index) is an index which measures the level of risk in the market when making investment decisions(Vuong et al., 2022). We aimed to determine the effect of the daily new cases and deaths due to the COVID-19 pandemic and the effect of the VIX index on the major stock markets during different stages of the pandemic period. In two of the mentioned countries, Italy and France, the number of reported deaths had a positive impact on the VIX returns. The VIX was down 0.54 points at 19.49 before the WHO declaring COVID-19 outbreak as a pandemic(Vuong et al., 2022). in overall, the VIX started to increase after the rise in the number of daily new cases and death. In March 2020, there was a peak of 85.47 in VIX index, which is the highest amount in the decade, while the number of cases and deaths peaked at the end of March 2020. After the highest peak the VIX index remained under the amount of 45 until September 2021(Prasad et al., 2022). Amon the different models that can be employed, in this paper we focus on ARCH model. ARCH is a statistical model which has attracted a lot of attention and has been used to solve the problem of how stock markets are affected by daily cases. this model is typically used to estimate the volatility of returns of stocks and market indices(Wang et al., 2021).

The rest of the paper is structured as follows. First we will examine the previous work and researches on the issue. Then data will be analyzed by figures and models and at the end there is going to be a concluding section.

2. Data and Methodology

2.1.Effect of the COVID-19 Pandemic on the VIX Index

The VIX index and daily new case and death numbers during the COVID-19 pandemic are provided in Figure1.

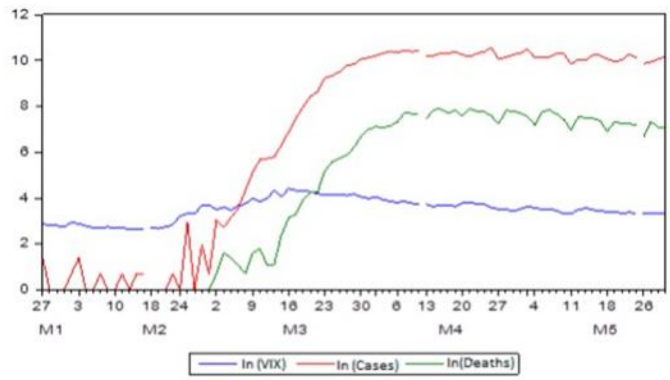


Figure1. Natural logarithms of the VIX index and daily new case and death numbers in the USA.

It can be noted from Figure 1 that the VIX index increased with the increase in the number of COVID-19 cases and death numbers in the USA. Furthermore, the VIX fear index started to increase with the first pandemic case in the USA. Moreover, the VIX index made a significant leap even when there were no deaths. The VIX index reached the highest level before the pandemic contamination and death figures peaked. This could have been because the COVID-19 case numbers were not always accepted as fact by some people. As the pandemic cases and death numbers became more and more evident, the level of fear began to drop from the peak. The VIX index reached its peak by mid-March 2020, while the number of cases and deaths peaked at the end of March 2020. On the other hand, by the third week of March, one could witness that the stock markets studied here fell to their lowest levels. To examine the relationship between the VIX index and daily new case and death numbers of the COVID-19 pandemic, we first needed to determine whether the time series was constant. The unit root properties of the time series used in the study were investigated using the unit root tests developed by Dickey and Fuller (1979) (augmented Dickey–Fuller (ADF)) and Phillips and Perron (1988) (PP). The unit root test results are given in Table 1.

Table 1. Unit root test results.

Variables	Augmented Dickey-Fuller (ADF) Test				Phillips-Perron (PP) Test				Stationary Level
	Level		Difference		Level		Difference		
	intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	
ln(VIX)	-1.43	-1.02	-10.81***	-11.06***	-1.45	-1.01	-10.66***	-10.89***	I(1)
ln(cases)	2.51	2.24	7.15***	18.24***	1.05	1.19	16.87***	17.38***	I(1)
ln(deaths)	-1.47	-1.54	-2.04	-2.21	-1.03	-047	-8.50***	-8.54***	I(1)

***** Indicates statistical significance at the 1% level.**

2.2.Estimates for different markets

Data analysis is a multi-step process during which the data is collected in different ways; They are summarized, categorized, and finally processed in order to provide the basis for establishing various types of analysis and connections between the data in order to test the hypotheses. In this process, the data are refined both conceptually and empirically, and various statistical techniques play a significant role in making conclusions and generalizations.

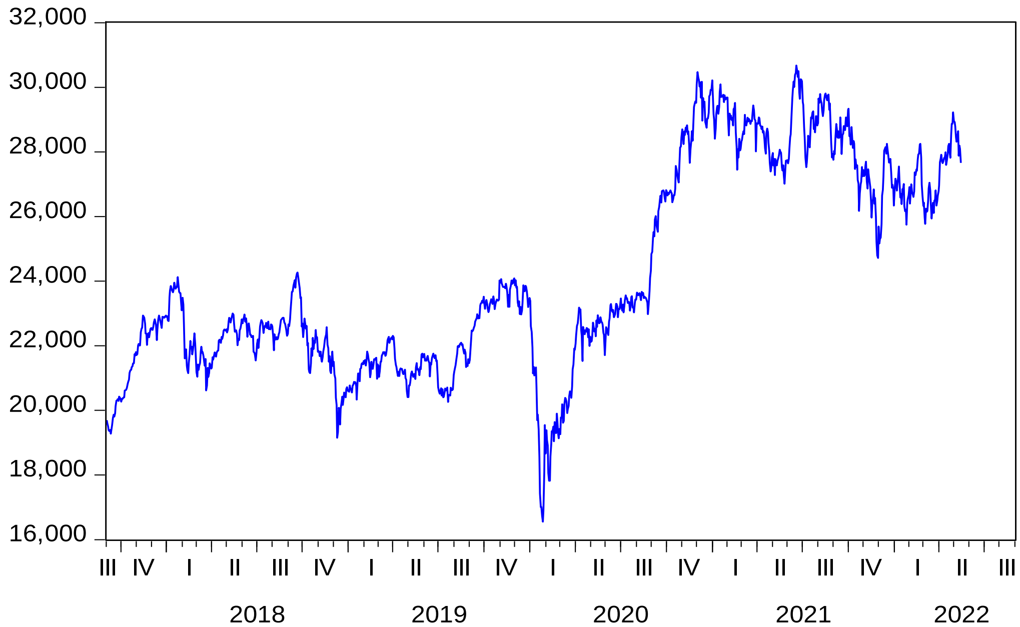
The method of testing the hypotheses of this research was carried out using the Arima econometric method and using the Eviews 9 software.

The time period from 2018 to 2022 is daily so that the impact of Corona can also be evaluated.

Table2 Introduction of model variables

Variable name	Symbol	Variable type
Pnikkie index	pnikkie	dependent

The variable(pnikkie) behavior over time is presented below:



2.3.Box and Jenkins display method

This method basically includes fitting an ARIMA model to the data. To produce a forecast based on an ARIMA model, after determining the final model, that is, determining the order of differentiation and determining the order of each of the AR and MA processes, it is necessary to know both the degree of stationarity (which was done in the previous part) and the degree of AR and MA, which is further determined by examining the correlation diagram.

In the Table 3 below, the correlation graph is presented :

	AC	PAC	Q-Stat	Prob
1	0.995	0.995	1216.5	0.000
2	0.989	-0.015	2420.3	0.000

3	0.983	-0.061	3609.8	0.000
4	0.977	0.029	4786.0	0.000
5	0.970	-0.056	5947.5	0.000
6	0.964	0.019	7095.0	0.000
7	0.958	0.005	8228.5	0.000
8	0.952	0.034	9349.4	0.000
9	0.946	-0.002	10458.	0.000
10	0.940	0.004	11554.	0.000
11	0.935	0.034	12638.	0.000
12	0.930	0.005	13712.	0.000
13	0.925	-0.027	14774.	0.000
14	0.919	-0.008	15825.	0.000
15	0.914	-0.006	16864.	0.000

Correlation chart has two parts autocorrelation and partial autocorrelation. The dashed line next to the permissible limit of changes shows that if the partial autocorrelation exceeds the permissible line, we have the MA process, and if the autocorrelation exceeds the permissible line, we have the AR process. The degree of violation also shows the desired degree for each case. In the above graph, it is clear that both autocorrelation and partial autocorrelation exceed the permissible limit, and according to the above graph, the degree of both is the same. Considering that stationarity was also of the first degree I(1), we can examine Box and Jenkins in the following.

It is determined from the correlation graph that the general results are presented below.

D(EXCHANGE RATE): ARIMA(1, 1, 1)

It means both AR(1) and MA(1) and once differentiation apply to the investigated variable.

3. Model estimation

The table below summarizes the initial estimate of the desired equation.

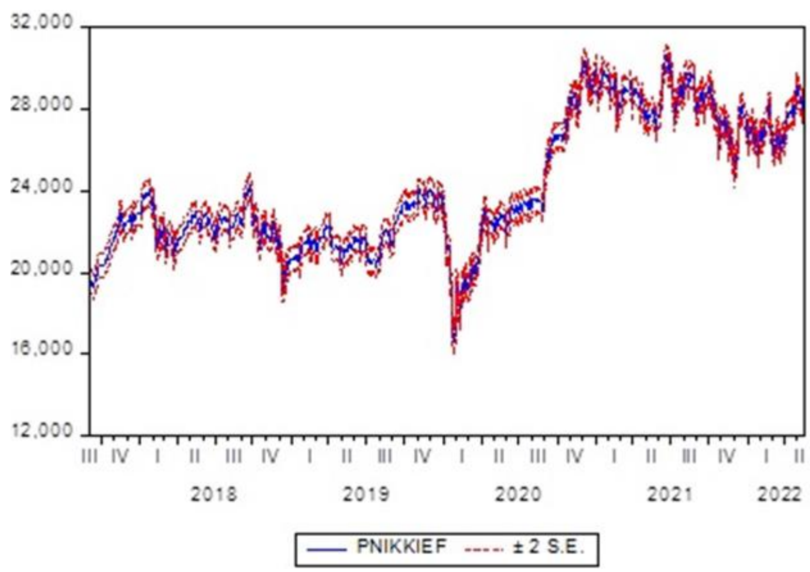
Table 3: ARIMA model estimation results of the research (dependent variable: pnikkie)

Variable	Coefficient	Std.Error	t-Statistic	Prob.

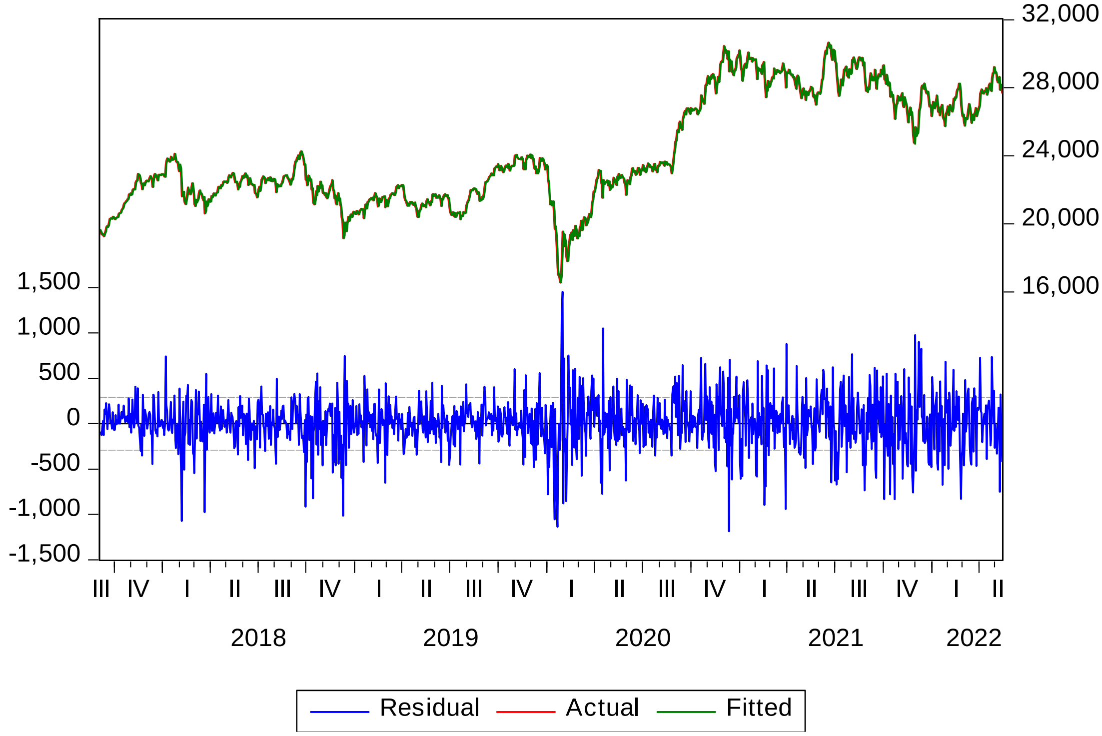
C	22072.42	6686.139	3.301221	0.0010
COVID	-789.3736	291.7345	-2.705794	0.0069
AR(1)	0.998472	0.002401	415.9176	0.0000
MA(1)	-0.003496	0.028734	-0.121655	0.9032

As can be seen, all the coefficients of the model (except the coefficient related to MA(1)) are significant with a probability of more than 95%. Therefore, the choice of AR(1) is correct and MA(1) is incorrect. Also, the coefficient of determination of 99% shows the almost complete explanation of the model by the variables. Corona variable is also quite significant.

The prediction of the variable value is presented below:



Below is the residual of the model:



If the residual has a specific shape, there is a possibility that the model has statistical problems. But in the diagram above, it is clear that the residual of the model does not have a specific shape and it is similar to a heart rhythm which is irregularly up and down, so the residual does not have a specific shape and the accuracy of the regression model is confirmed once again.

ARCH estimate is also presented below:

Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	27355.20	2839.438	9.634018	0.0000
COVID	-761.6123	1678.698	-0.453692	0.6501
AR(1)	0.996001	0.002297	433.5896	0.0000
Variance Equation				
C(4)	96819	25047.16	3.865482	0.0001
C(5)	0.989780	0.004505	219.6937	0.0000
C(6)	0.50142	0.011576	4.331503	0.0000
C(7)	0.109605	0.031874	3.438656	0.0006

C(8)	0.413141	0.199314	2.072813	0.0382

Corona is significant in the Arima model, but it is meaningless in the Arch model, because the Arch model removes the main and general fluctuations, and the outbreak of Corona caused a shift in the model and a fundamental fluctuation in the work, which is removed here.

3.1 Estimation of the FTSE index

In the following, the same procedure for the FTSE index is repeated and presented in the same way as the previous estimates:

A) Arima estimation

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	7340.972	350.2868	20.95703	0.0000
COVID	25.40916	72.74553	0.349288	0.7269
AR(1)	0.993450	0.003701	268.4591	0.0000
MA(1)	-0.023578	0.028552	-0.825810	0.4091

B) Arch estimate

C) Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	7291.050	186.2991	39.13627	0.0000
COVID	-7.773495	94.79052	-0.082007	0.9346
AR(1)	0.989726	0.003818	259.2223	0.0000
Variance Equation				
C(4)	4806.323	596.8483	8.052839	0.0000
C(5)	0.970486	0.007737	125.4404	0.0000
C(6)	0.070091	0.011731	5.975099	0.0000
C(7)	0.110050	0.029599	3.718050	0.0002
C(8)	-0.411489	0.136679	-3.010618	0.0026

For FTSE in both Arch and Arima models, the spread of Corona is not significant.

3.2 Estimation of the CAC index

In the following, the same procedure for the CAC index is repeated and presented in the same way as the previous estimates:

A) Arima estimation

B) Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	5680.019	370.9585	15.31174	0.0000
AR(1)	0.994832	0.002813	353.6749	0.0000
MA(1)	0.008068	0.028143	0.286687	0.7744

C) Arch estimation

Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	6480.434	680.503	9.529345	0.0000
COVID	79.61567	348.8690	0.228211	0.8195
AR(1)	0.994676	0.003075	323.4697	0.0000
MA(1)	0.009243	0.031488	0.293538	0.7691
Variance Equation				
C(4)	17363.15	646.2000	26.86962	0.0000
C(5)	0.999544	2.17E-05	46125.41	0.0000
C(6)	-0.020976	0.006264	-3.348635	0.0008
C(7)	0.210467	0.023649	8.899720	0.0000
C(8)	0.732316	0.028205	25.96422	0.0000

For CAC in both ARCH and ARIMA models, the spread of Corona is not significant.

3.3 Estimation of the ASX index

In the following, the same procedure for the ASX index is repeated and presented in the same way as the previous estimates:

A) Arima estimation

Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	6304.239	671.9967	9.381354	0.0000
COVID	28.34426	64.83721	0.437160	0.6621

AR(1)	0.997265	0.002494	399.8656	0.0000
MA(1)	-0.097679	0.028338	-3.446894	0.0006

B) Arch estimation

Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	7552.668	1137.112	6.641972	0.0000
COVID	33.41924	515.7914	0.064792	0.9483
AR(1)	0.997088	0.002451	406.8876	0.0000
Variance Equation				
C(4)	437529.2	317816.8	1.376671	0.1686
C(5)	0.999975	2.93E-05	34157.10	0.0000
C(6)	0.017481	0.012081	1.446941	0.1479
C(7)	-1.256716	8.424578	-0.149173	0.8814
C(8)	0.165321	0.021109	7.831655	0.0000
C(9)	0.786094	0.031569	24.90082	0.0000

For ASX in both Arch and Arima models, the prevalence of Corona is not significant.

3.4 Estimation of the SPNZX index

In the following, the same procedure for the SPNZX index is repeated and presented in the same way as the previous estimates:

A) Arima estimation

Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	59732.76	453.5307	131.7061	0.0000
COVID	16148.01	634.0584	25.46771	0.0000
AR(1)	0.002500	1.510291	0.001655	0.9987
MA(1)	0.002500	1.518106	0.001647	0.9987

B) Arch estimation

Variable	Coefficient	Std.Error	z-Statistic	Prob.

C	-4754.771	80186.09	-0.559297	0.9527
COVID	-286.6500	15739.47	-1.018212	0.9855
AR(1)	1.000625	0.000725	1379.887	0.0000
Variance Equation				
C(4)	150562.7	26683.76	5.642486	0.0000
C(5)	0.994585	0.001496	664.6890	0.0000
C(6)	0.018400	0.005982	3.075950	0.0021
C(7)	0.091358	0.012473	7.324195	0.0000
C(8)	0.830321	0.028695	28.93592	0.0000

It is not significant for the SPNZX index in the Arch model of Corona prevalence. But in the Arima model, the spread of Corona is quite significant.

4. Conclusion

In conclusion, our comprehensive investigation into the relationship between daily COVID-19 case numbers and the stock market indices of developed countries, utilizing both ARIMA and ARCH models, has yielded valuable insights. The study unequivocally established the substantial impact of the COVID-19 pandemic on the stock market in the United States. This impact manifested as heightened market volatility and, at times, diminished returns. The CBOE Volatility Index (VIX) emerged as a crucial indicator, displaying a consistent positive correlation with daily COVID-19 case counts, reflecting increased market risk perception as the pandemic unfolded. While our ARIMA model detected significant statistical relationships between COVID-19 cases and stock market performance in certain instances, the ARCH model introduced a nuanced perspective, suggesting that market fluctuations were rooted in fundamental shifts, extending beyond the direct influence of daily case numbers. Furthermore, the variation in each country's market response underscored the influence of diverse economic structures, government interventions, and public sentiment on market outcomes. Importantly, our research has identified a notable gap in the literature concerning the specific impact of COVID-19 on the VIX index and stock markets, particularly within the context of U.S. data, signaling the need for further exploration in this area.

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