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## 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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ARTICLE INFO	ABSTRACT
<p>Article History:            Received 8 July 2023            Received in revised form 16 September 2023            Accepted 15 November 2023            Available online 3 December 2023</p>	<p>The global economy is grappling with heightened uncertainty due to the ongoing Coronavirus pandemic. The daily reported cases of the virus have emerged as a critical factor shaping market sentiment and investor behavior. As the virus continues to spread, impacting various sectors, stock markets are witnessing considerable volatility. It becomes imperative for investors, policymakers, and analysts to comprehend the intricate relationship between daily COVID-19 cases and stock market indices. ARIMA, a widely-used time series analysis technique, proves invaluable in modeling and predicting future movements in stock market indices. Particularly effective for data exhibiting non-stationarity, seasonality, and autocorrelation, ARIMA leverages historical data on daily COVID-19 cases and stock market indices to identify patterns, trends, and make forecasts about future market movements. Complementing ARIMA, ARCH models are tailored to capture the volatility clustering and heteroskedasticity often observed in financial time series data. Given the heightened market volatility induced by the Coronavirus pandemic, ARCH models prove useful in modeling this volatility and making forecasts about future market volatility based on daily COVID-19 cases. By synergistically employing ARIMA and ARCH models, a comprehensive understanding of the intricate relationship between daily COVID-19 cases and stock market indices emerges. This paper delves into the impact of COVID-19 spread in Japan, Australia, France, Britain, and the United States, employing autoregressive integrated moving average (ARIMA) and autoregressive conditional heteroskedasticity (ARCH) methods. Statistical significance of COVID-19 confirmed cases is established, contributing to volatility modeling, as demonstrated by information criteria and forecasting accuracy measures.</p>
<p>Keywords:            COVID-19 Pandemic, Co-Integration Test, ARIMA Method, ARCH Method, Stock Markets</p>	

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## **1. INTRODUCTION**

In 2019, a new public health crisis began to threaten the world. It originated in China, with new cases identified in Wuhan city [1]. In early 2020, additional cases appeared in various European countries. By March 2020, the World Health Organization (WHO) had declared COVID-19 a pandemic. This widespread disease has created disastrous consequences for people's socio-economic status. In addition to public health, the pandemic has also impacted numerous economic sectors, including the stock market which is particularly vulnerable. Both positive and negative news related to COVID-19 can have an impact on the stock market. However, negative news appears to have a greater impact, suggesting that an increase in COVID-19 cases generally has a negative effect on the market [2]. Investors exhibited signs of fear upon observing the rise in confirmed COVID-19 cases, and their impulsive behavior resulted in unexpected drops in the stock market [3]. Volatility is a measure of the dispersion of returns in various markets, including the stock market. It is important for investors to be aware of the impact of financial crises caused by disasters, such as COVID-19, on the market's condition. Therefore, governments around the world have been using various methods to assess and maintain the health of their economies [4]. The objective of this project is to analyze the impact of the pandemic and daily infection rates on the volatility and returns of the stock market in select countries, including Japan, Australia, Britain, France (representing the Euro area), and the United States [5]. The impact of the virus varied across countries, and their stock markets responded differently to changes in the number of deaths and infections.

In the United States, job losses have reached an unprecedented high, with over 10 million people already out of work [6]. According to VAR models, the number of reported deaths in Italy and France has a negative impact on stock market returns. The CBOE Volatility Index (VIX) measures the level of risk in the market when making investment decisions [7]. The objective of this study was to investigate the relationship between daily new cases and deaths caused by the COVID-19 pandemic and the VIX index's effect on major stock markets during different stages of the pandemic. The impact of reported deaths on the VIX returns was found to be positive in Italy and France. Before the WHO declared the COVID-19 outbreak a pandemic (Vuong et al., 2022), the VIX was down 0.54 points at 19.49. Overall, the VIX began to increase following the rise in daily new cases and deaths. In March 2020, the VIX index peaked at 85.47, the highest amount in a decade, while the number of cases and deaths peaked at the end of the same month. After the highest peak, the VIX index remained below 45 until September 2021 [8]. Among the different models that can be employed, this paper focuses on the ARCH model. ARCH is a statistical model that has attracted a lot of attention and has been used to solve the problem of how daily cases affect stock markets. This model is typically used to estimate the volatility of returns of stocks and market indices [9]. The rest of the paper is structured as follows: first, we will examine previous research on the issue. The data will be analyzed using figures and models. Finally, a concluding section will be presented.

## **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 Figure 1. Figure 1 shows that the VIX index increased as the number of COVID-19 cases and deaths in the USA increased. The VIX fear index began to rise with the first pandemic case in the USA and made a significant leap even before any deaths occurred. The VIX index reached its highest level before the peak of the pandemic's contamination and death figures. The decrease in fear levels during the COVID-19 pandemic may be attributed to the increasing acceptance of case and death numbers. The VIX index peaked in mid-March 2020, while the number of cases and deaths peaked at the end of March 2020. Additionally, the stock markets studied here fell to their lowest levels by the third week of March. To investigate the relationship between the VIX index and the daily new cases and death tolls of the COVID-19 pandemic, we first needed to determine if the time series was constant. We used the unit root tests developed by Dickey and Fuller (1979) (augmented Dickey-Fuller (ADF)) and Phillips and Perron (1988) (PP) to examine the unit root properties of the time series used in the study. The results of the unit root tests are presented in Table 1.

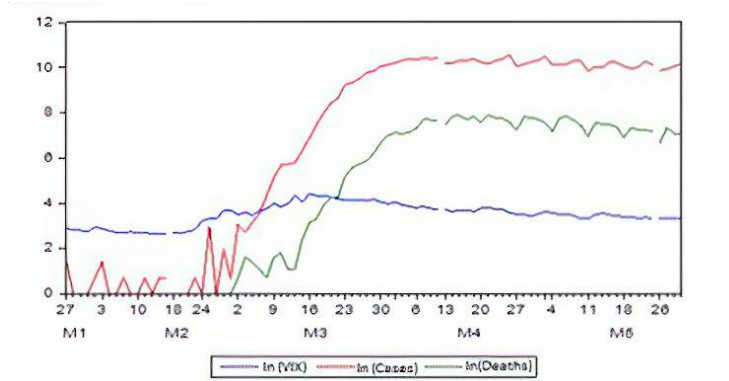


Fig.1. Natural logarithms of the VIX index and daily new case and death numbers in the USA.

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	-	-10.89***	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. The data is collected in various ways, summarized, categorized, and processed to establish different types of analysis and connections between the data to test hypotheses. Conceptually and empirically, the data is refined, and statistical techniques play a significant role in making conclusions and generalizations.

The hypotheses of this research were tested using the Arima econometric method and Eviews 9 software. The time period from 2018 to 2022 is daily so that the impact of Corona can also be evaluated.

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



Fig. 2. The variable(pnikkie) behavior over time

**Table 2.** Introduction of model variables

Variable name	Symbol	Variable type
Pnikkie index	pnikkie	dependent

### 2.3. Box and Jenkins display method

This method involves fitting an ARIMA model to the data. To produce a forecast based on an ARIMA model, it is necessary to determine the final model, including the order of differentiation and the order of each of the AR and MA processes. This requires knowledge of both the degree of stationarity (which was determined in the previous part) and the degree of AR and MA, which is further determined by examining the correlation diagram. In the Table 3, the correlation graph is presented:

**Table 3.** The correlation graphs

	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

The correlation chart consists of two parts: autocorrelation and partial autocorrelation. The dashed line represents the permissible limit of changes. If the partial autocorrelation exceeds this line, it indicates the presence of the MA process. If the autocorrelation exceeds the permissible line, it indicates the presence of the AR process. The degree of violation also indicates the desired degree for each case. The graph above shows that both autocorrelation and partial autocorrelation exceeds the permissible limit and have the same degree. Since stationarity was also of the first degree I(1), we can further examine Box and Jenkins.

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.

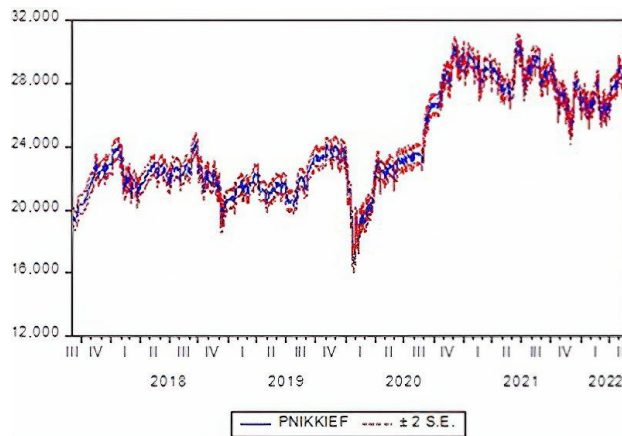
### 3. MODEL ESTIMATION

The table 4 summarizes the initial estimate of the desired equation.

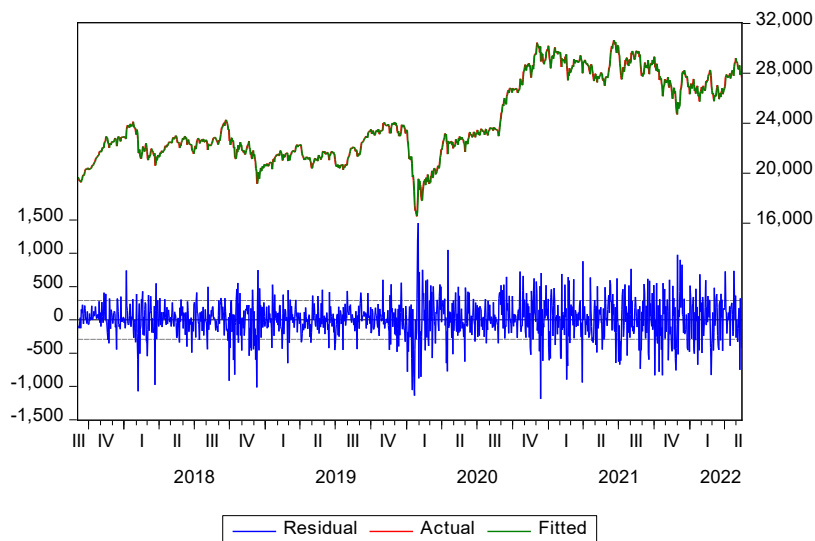
**Table 4.** ARIMA model estimation results of the research (dependent variable: pnikkie)

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

The statistical analysis reveals that all coefficients in the model attain statistical significance at a confidence level exceeding 95%, with the exception of the coefficient linked to MA(1). Consequently, the choice of AR(1) is deemed appropriate, while MA(1) is considered unsuitable. Furthermore, the high coefficient of determination, reaching 99%, indicates an almost exhaustive explanation of the model by the variables. Remarkably, the variable representing the impact of the Coronavirus demonstrates considerable significance in the model. Figure 3 illustrates the prediction of the variable value, while Figure 4 depicts the residuals of the model.



**Fig. 3.** The prediction of the variable value



**Fig. 4.** the residual of the model

When examining residuals, the presence of a distinct pattern may signal potential statistical issues with the model. However, upon inspection of the provided diagram, it becomes evident that the residuals do not follow a specific pattern. Instead, they exhibit an irregular up-and-down rhythm, resembling a heartbeat. This absence of a discernible

pattern in the residuals reinforces the accuracy of the regression model, affirming its reliability. The ARCH estimate is also presented in Table 5.

**Table 5.** ARCH estimate

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

The contrasting significance of the variable "Corona" in the ARIMA and ARCH models stems from the inherent differences in their approaches. The ARCH model is designed to filter out overarching and general fluctuations, aiming to capture more specific and localized volatility patterns. The outbreak of Corona led to a significant shift in the model, accompanied by a fundamental fluctuation in the data.

However, this specific fluctuation induced by the Corona variable is addressed and removed within the ARCH model. As a result, the variable "Corona" becomes statistically insignificant in this context. The ARCH model's focus on volatility patterns specific to the financial time series may downplay the significance of broader events, such as the Corona outbreak, in explaining the variability in the data.

### 3.1. Estimation of the FTSE index

In the subsequent analysis, the identical procedure for the FTSE index is replicated and presented in a manner consistent with the prior estimates. Table 6 provides the ARIMA estimation results, while Table 7 presents the ARCH estimates.

**Table 6.** Arima estimation for the FTSE

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

**Table 7.** Arch estimate for the FTSE

A) 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 subsequent analysis, the identical procedure for the CAC index is replicated and presented in a manner consistent with the previous estimates. Table 8 displays the ARIMA estimation results for the CAC, while Table 9 presents the ARCH estimates for the CAC.

**Table 8.** Arima estimation for the CAC

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

**Table 9.** Arch estimation for the CAC

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 subsequent analysis, the identical procedure for the ASX index is replicated and presented in a manner consistent with the previous estimates. Table 10 displays the ARIMA estimation results for the ASX index, while Table 11 presents the ARCH estimates for the ASX index.

**Table 10.** Arima estimation for the ASX index

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

**Table 11.** Arch estimation for the ASX index

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 subsequent analysis, the same procedure for the SPNZX index is replicated and presented similarly to the previous estimates. Table 12 displays the ARIMA estimation results for the SPNZX index, while Table 13 presents the ARCH estimates for the SPNZX index.

**Table 12.** Arima estimation for the SPNZX

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

**Table 13.** Arch estimation for the SPNZX

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 summary, our comprehensive investigation into the relationship between daily COVID-19 case numbers and stock market indices of developed countries, utilizing both ARIMA and ARCH models, has provided valuable insights. The study has conclusively demonstrated the significant impact of the COVID-19 pandemic on the United States stock market, marked by increased market volatility and, at times, diminished returns. The CBOE Volatility Index (VIX) emerged as a crucial indicator, consistently exhibiting a positive correlation with daily COVID-19 case counts, indicating heightened market risk perception during the progression of the pandemic.

While our ARIMA model identified statistically significant relationships between COVID-19 cases and stock market performance in specific instances, the ARCH model introduced a nuanced perspective. It suggested that market fluctuations were rooted in fundamental shifts extending beyond the direct influence of daily case numbers.

Furthermore, the variations in each country's market response underscored the impact of diverse economic structures, government interventions, and public sentiment on market outcomes. Importantly, our research has identified a notable gap in the existing literature regarding the specific impact of COVID-19 on the VIX index and stock markets, particularly within the U.S. data context. This signals the necessity for further exploration in this area to enhance our understanding of the complex dynamics at play.

## **CONFLICTS OF INTEREST**

The authors declare no conflict of interest.

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