DETERMINING THE RETURN VOLATILITY OF MAJOR STOCK MARKETS BEFORE AND DURING THE COVID-19 PANDEMIC BY APPLYING THE EGARCH MODEL

Abstract
With this study, we aim to determine the effect of the Covid-19 pandemic on the return volatility of the DJI, the DAX, the FTSE100 and the CAC40 stock indexes. We take return volatility between 1st January 2019 and 17th July 2020 and split it into two separate periods - before the Covid-19 pandemic outbreak and the first wave of the 'In-Pandemic' period. Only the so-called first wave of the pandemic was chosen to avoid the influence of knowledge of possible vaccines and antiviral solutions. Data were analysed by using the exponential GARCH (EGARCH) model. Findings show excessive volatility in the major stock markets with short volatility persistence and the presence of leverage in returns during the first wave of the Covid-19 pandemic outbreak. Moreover, during the pandemic period, positive shocks have been observed to have a greater effect than negative socks on the stock index return volatility.
Keywords: Corona Virus (COVID-19); Pandemics; Return Volatility; Stock Indexes; EGARCH
JEL Classification: E44, G19, G41

1. Introduction

COVID-19 is an infectious disease caused by a newly discovered coronavirus. As reported by the World Health Organization (WHO), most people infected with the COVID-19 virus will experience mild to moderate respiratory illness and recover without requiring special treatment (WHO, 2020). The first case of the coronavirus in China in December 2019 has quickly expanded into the global outbreak of the Covid-19 pandemics with more than half a million infected people and 16% of death cases on March, 20th, 2020 (Worldometer, 2020). The pandemic outbreak has affected all industries and the stock market around the world. The Covid-19 outbreak brought uncertainty and general distress, which caused the substantial decline of the Shanghai stock market by 8 % on February 3rd, 2020. This disruption rapidly spread to other international stock markets resulting in, for example, a decline in the US stock prices, including plummeting of the Standard & Poor's 500 Index (S&P index) and the Dow Jones Industrial Average Index (DJIA) by 4.4%. Despite, many countries have ignored the rapid propagation of the virus at the beginning of 2020; the Covid -19 has started to raise serious concerns due to its rapid spread outside China (Albulescu, 2020). Some analysts such as Elliot (2020) even saw the parallels to the crisis of 1929, noting that Covid-19 is "unprecedented", with record levels of leverage and overbought stocks. Chevallier (2020) suggested there will be a cataclysmic impact of the pandemics on the financial markets and expects a severe recession. Besides, the world real GDP growth in 2020 was revised by many institutions such as Goldman Sachs and IHS Markit to less than 2% forecasting the possible global recession (Isaac, 2020).

This uncertainty and panic in the markets have affected the stock market in different ways and despite the expected general plunge of major stock markets, other stocks, for example, Campbell Soup Company (CPB), Zoom Video Communications (ZM), Teladoc Health, Inc. (TDOC), Domino Pizza (DPZ), The Clorox Company (CLX), Virtu Financial, Inc. (VIRT) and Everbridge, Inc. (EVBG) benefited by providing an alternate market universe, defined by Desjardins (2020) as "The Pandemic Economy".

Although several studies have focussed on stock market volatility, the behaviour of investors in stock markets, price and return fluctuations, market trading volume and general behaviour of the world stock markets, this pandemic (Covid-19) has disrupted the world in an unprecedented manner and a study on the change in the return volatility of major stocks during this early distressed period would help in understanding the effect of the pandemic fear when the world is still uncertain of the outcome and pandemic fatigue has not yet kicked in (i.e. whether there will be a vaccine or antiviral medicine to ensure a quick return to normality).

2. Objective of the study

Therefore, following the topicality of the Covid-19 pandemic outbreak in the world the uncertainties during this "Pandemic Economy", we aim to determine the impact of the negative news of Covid-19 cases and deaths on the return volatility of the stock market indexes specifically, the DJIA, the Deutscher Aktienindex (DAX), the Financial Times Stock Exchange 100 Index (FTSE100) and the Cotation Assistée en Continue (CAC40). To identify the impact of the uncertainties following the pandemic outbreak, we study the periods before the pandemic period started in the United States of America (US) and Europe (from the 1st January 2019 to the 31st December 2019) and in the so-called first wave of the in-pandemic period (2nd January 2020 to 17th July 2020). The analysis of the impact of uncertainties following the pandemic outbreak on the major stock market indexes allows us to determine its' impact on the major stock markets representing the USA (DJIA), Germany (DAX), the UK (FTSE100) and the French (CAC40). The determination of the impact of uncertainty following the pandemics is important for both non-professional and professional investors, including, policymakers, portfolio and fund managers as well as risk managers, underwriters, actuaries, and other professionals who are responsible for the portfolio diversification and portfolio management decisions.

3. Literature Review

There is a growing literature that not only relates to past pandemics such as HIV/AIDS, SARS but opens up to the current, still ongoing COVID-19. However, only a few studies have placed their focus on the impact these pandemics have on the major markets. Pandemics such as HIV/AIDS affected economic units such as businesses, households and government, the labour supply decisions, labour efficiency and household income. Budgets deficits orphaned by AIDS increased in certain countries because of higher business costs, public expenditure on health care and support of disabled and children (Haacker 2004). Kauffman and Weerapana (2006) and Daly et al (2019) demonstrated that the bad news related to HIV/AIDS in the Republic of South Africa had a negative effect on the exchange rate of the South African Rand against the U.S. Dollar. Lee and McKibbin, (2004), demonstrated that the SARS epidemic affected significantly various economies, because of the reduction in the demand for various goods and services, increased operating costs and country risks, which in turn increased the risk premiums. This had an impact on a global scale in 2003 although the count of infected persons and deaths, in this case, was not the same in all countries.

According to Loh (2006), although, with no significant long-run implications the SARS pandemic increased the volatility in the airline stocks with lower mean returns in certain countries. Fernandes (2020), for example, explains that COVID-19 has a global effect and that this major difference from previous pandemics, is that this pandemic brings the world together, creating a spill-over effect throughout the supply chains and causing disruption in the balance of supply and demand. Moreover, he argues that some well-known companies have seen their stock prices fall drastically in a few days and shows that the US and British markets have seen their worst performance ever with over 25% and 35% downfall respectively. He continues to argue that the impact of Covid-19 is being underestimated and suggests that in a mild scenario, GDP will take a 3 to 5% hit depending on the country and that service-oriented and tourism reliant economies will specifically be negatively affected with the largest job losses.

Singh et al., (2020), using panel data analysed the impact of the COVID-19 outbreak on the stock markets of G-20 countries 150 days before and 58 days post the COVID-19 outbreak news release in the international media. They noted a cumulative average abnormal return during the first 43 days as a consequence of increased panic in the stock markets resulting from an increased number of COVID-19 positive cases. However, they note a recovery after that date.

Using the global hybrid Dynamic Stochastic General Equilibrium (DSGE) Models and Computable General Equilibrium (CGE) Models developed by McKibbin and Wilcoxen (1999, 2013), McKibbin and Fernando (2020), calculated the impact of the outbreak of Covid-19 while still only in China, on the global economy. They show that this impact on the financial risk, even with a control in the United States (US) was higher in relation to the (2*21)G-20 and OECD countries and lower than England and several developing countries

Another study by Albulescu (2020a and 2020b) noted that following the outbreak of the COVID-19; the long-run price of crude oil was impacted negatively by the news of COVID-19 infections and noted that there was an indirect effect on crude oil prices when the volatility of the financial markets is amplified.

Moreover, Bahrini and Filfilan (2020) found a negative response of the stock markets in the GCC (Gulf Cooperation Council) countries to the COVID-19 confirmed deaths. The analysis has shown that the daily returns of the major stock market indices in these countries have declined during the increasing number of confirmed deaths.

Zeren and Hızarcı (2020), used data between January 23rd, 2020 and March 13th, 2020, to study the co-integration relationship between Covid-19 cases and some selected stock markets. They demonstrated the existence of a co-integration relationship between the Covid-19 cases and the Shanghai Stock Exchange (SSE), the Korea Composite Stock Price Index (KOSPI) and the Índice Bursátil Español (IBEX35) and no relationship with the FTSE 100, Milano Indice di Borsa (MIB), the CAC40 and the DAX30; which revealed that there is a geographical effect of Covid-19 on stock markets as the virus spread to the European countries during March.

Moreover, Ramelli and Wagner (2020a) demonstrate that the outbreak of Covid-19 in China and the US brought about increases in the returns of sectors related to Telecom Services, Health care and Software services and decreases in sectors such as energy, transportation, insurance, real estate, retailing and automobiles. They explained that the reaction to concerns related to Covid-19 by the Chinese and the US stock markets was swift due to investors' concern regarding corporate debt and liquidity, which was expected to mutate in an economic crisis augmented through financial channels (Ramelli and Wagner 2020b).

Kinateder et al. (2021) showed that the Covid-19 pandemic similarly to the financial crises, created fear amongst investors. They found that gold, U.S., UK, and German sovereign bonds were considered as a safe option for investors during that period. Also, Hassan et al. (2021) compared the safe-haven properties of various assets with the major Gulf Cooperation Council (GCC) stock indexes during two periods during the financial turmoil; specifically the COVID-19 pandemic and the 2008 Global Financial Crisis (GFC) periods. They found that sovereign bonds offered the highest hedging benefits under both crises. The traditional safe assets, gold and silver, which were reasonably productive under the GFC, have been less so during the pandemic. Moreover, they noted that the Japanese yen emerged as a safe choice for investors holding GCC stock indexes and that both sector indexes and stock indexes failed to safeguard investors most of the time during each crisis.

4. Methodology

To carry out this study we used the exponential GARCH (EGARCH) model developed by Nelson (1991). This since, although we could have used other models, such as the Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) to understand better the dynamic properties of financial time series and for predicting heteroskedasticity over time and a later mode the GARCH (Generalized ARCH) model, developed by Bollerslev (1986), which is based on the weighting of past error squares; they assume the same effect on the volatility of financial assets for positive and negative shocks in the financial markets. In addition, these models, are only concerned with the magnitude of volatility, and the sign of volatility is ignored.

As noted by Black (1976), it is frequently observed in the financial markets that negative news (negative shocks) affect volatility more than positive news of the same size (positive shocks). This situation, which is expressed as the leverage effect, cannot be detected with ARCH / GARCH models. The EGARCH model allows for a more appropriate analysis of the asymmetry effect in the volatility of the time series. The most important feature of this model is that it allows the modelling of asymmetric effects in estimates by eliminating the non-negative constraint in GARCH models. The EGARCH model proposed by Nelson (1991) is expressed as follows:

$$log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \, log(h_{t-j}) \; + \; \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} \; + \; \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} \qquad (1)$$

In the model, h_t shows the conditional variance, h_{t-j} shows the values of the conditional variance going back j periods, u_{t-i} shows the values of the error terms going back i periods. ω, β_j, α_i and γ_i are EGARCH model parameters. The presence of asymmetric volatility in the EGARCH model depends on the statistically significant γ_i parameter. The γ_i parameter shows both the leverage effect and the asymmetry of the series. In the model, if $\gamma_i = 0$, it means that a positive shock and a negative shock have the same effect on volatility. If $\gamma_i \neq 0$, it indicates the presence of an asymmetric effect in the series. If $-1 < \gamma_i < 0$, a negative shock increases volatility more than a positive shock. (Brooks, 2008:406).

5. Data

In the study, we studied the effect of the Covid-19 Pandemic on the stock market volatility of the DJIA, DAX, FTSE100 and CAC40 stock indices. The choice of this sample was based on the reasoning that the latter three markets are the most popular European stock market indexes, while the former market is representative of one of the most popular markets in the US. They are seen as a proxy for the broader market (Kuepper, 2020). The data set used in this study consists of daily closing price data from 1st January 2019 to the 17th July 2020 and was divided into two sub-periods: The pre-pandemic period - 1st January 2019 to 31st December 2019 and the in-pandemic period 2nd January 2020 to 17th July 2020. This data was collected using the "www.investing.com" Logarithmic returns of stock indices calculated using the formula $R_t=\ln(P_t/P_{t-1})$. Graphs during the period of study of the DJIA, DAX, FTSE100 and CAC40 returns are shown in Figures 1, 2, 3 and 4.

When the figures of the stock index return are analysed, we note that there are fluctuations in all stock index returns shortly after the Covid-19 pandemic appears. This highlights that stock indices are affected by the Covid-19 pandemic. Descriptive statistics of the index return series are shown in Table 1.

[Insert Figures 1, 2 and 3 and Table 1 Here]

According to the Jarque-Bera test statistics of the stock index return series in all periods, the series does not have a normal distribution. The rejection of the normality test based on the Jarque-Bera test provides evidence of the presence of GARCH effects. The Augmented Dickey-Fuller (ADF) unit root test developed by Dickey and Fuller (1979) and Phillips and Perron (PP) unit root test developed by Phillips and Perron (1988) were used for the stationary analysis of the series. The results of the unit root tests, both ADF and PP tests, showed that the series does not have unit root in all periods. The null hypothesis that the unit root exists in the series is therefore rejected. Thus, it is concluded that the level values of the series are stationary I(0).

6. Findings

After determining that the stock index return series are stationary in the level values, we determined whether heteroskedasticity is present in the series to model the volatility of the series. We first determine the autoregressive moving average (ARMA) model structure, which is the linear stationary stochastic model of the return series. The most suitable ARMA models for return series are determined according to Akaike Information Criteria (AIC), Schwartz Information Criteria (SCI) and Log-Likelihood ratio and are shown in Table 2. The most suitable ARMA models of DJIA, DAX, FTSE100 and CAC40 stock index return series were determined separately in all periods. Then, autocorrelation and ARCH LM tests were performed until the 10th lag to determine whether there is heteroskedasticity in the return series. The results of the tests are provided in Table 2.

[Insert Table 2 Here]

According to Ljung-Box Q^2 statistics and ARCH LM test results, all return series were statistically significant until the 10th lag, except for the pre-pandemic period of DAX and FTSE100 stock index returns. These findings show that there is heteroskedasticity in the return series, that is, an ARCH effect. At this stage, the volatility of the return series needs to be estimated.

For the most suitable EGARCH model estimation, we must first establish that parameters are statistically significant and parameter constraints provided. Then we must determine that the sum of the variance equation coefficients of conditional heteroskedasticity models are less than one. Among the models that meet these parameter criteria, the model with a low likelihood ratio (AIC), a Schwartz Information Criterion (SIC) and a log-likelihood ratio are chosen as the most suitable model.

The results of the EGARCH models determined as the most suitable model according to the criteria are given in Table 3.

[Insert Table 3 Here]

The parameters of the EGARCH models estimated for the return series are statistically significant. α represents the ARCH parameter, β represents the GARCH parameter and γ represents the leverage parameter in the model.

Large values of the ARCH and GARCH parameters influence conditional volatility in different ways. A high ARCH parameter implies that the effects of a shock are more pronounced in the subsequent period. In contrast, a high GARCH parameter implies that the effects of a shock are more persistent (Enders, 2004: 134). Therefore, the large ARCH value will increase volatility in the short term, and the large GARCH value will increase volatility in the long term (Nazlıoğlu et al. 2013). In the EGARCH model, the effect of good news on volatility in the financial markets is calculated as $\alpha + \gamma$, and the effect of bad news on volatility in the financial markets is calculated as $\alpha - \gamma$ (Lin, 2017). To determine how many days the volatility of the financial time series continues, the HL (Half-Life) measure can be determined based on the equation $HL = \ln(0.5) / \ln(\beta)$ (Kalaycı et al., 2010).

The status of DJIA, DAX, FTSE100 and CAC40 stock index return volatility in all periods is shown in Table 4.

[Insert Table 4 Here]

EGARCH models predicted for the DJIA, the DAX, the FTSE100 and the CAC40 stock index returns show the presence of leverage in the returns.

For the DJIA, the DAX, the FTSE100 and the CAC40 index returns, it was determined that good news in the stock market positively affects the return volatility by 7.14%, and bad news positively affects the return volatility by 42.32%. When the DJIA index return volatility persistence was examined, it was determined that the effect of volatility continued for approximately 28 days. In the ‘Pre-Pandemic period’, one could note that good news in the stock market negatively affected the DJIA index return volatility by 45.05% and positively affected the DJIA index return volatility by 10.27%. On the other hand, in the ‘In-Pandemic’ period good news positively affected the DJIA index return volatility by 10.27% and bad news by 46.02%. When the DJIA index return volatility permanence is examined, it is determined as 19 days in the Pre-Pandemic period and 11 days in the In-Pandemic period.

For the DAX index returns, it was determined that good news in the stock market negatively affects the return volatility by 2.98%, and bad news positively affects the return volatility by 33.22%. When the DAX index return volatility persistence was examined, it was determined that the effect of volatility continued for approximately 32 days. In the ‘In-Pandemic period’, it was observed that good news in the stock market negatively affected the DAX index return volatility by 39.49%, and the bad news positively affected the return volatility by 5.89%. When the volatility permanence of the DAX index return was examined, it was determined as approximately 32 days in the In-Pandemic period.

For the FTSE100 index returns, one could note that good news in the stock market negatively affects the return volatility by 8.36%, and bad news positively affects the return volatility by 23.95%. When the FTSE100 index return volatility persistence was examined, it was determined that the effect of volatility continued for approximately 35 days. In the ‘In-Pandemic period’, it was observed that good news in the stock market negatively affected the FTSE100 index return volatility by 44.06%, and the bad news positively affected the return volatility by 4.77%. When the volatility permanence of the FTSE100 index return is examined, it is determined as approximately 16 days in the In-Pandemic period.

For the CAC40 index returns, one could note that good news in the stock market positively affects the return volatility by 0,58%, and bad news positively affects the return volatility by 41.63%. When the CAC40 index return volatility persistence was examined, it was determined that the effect of volatility continued for approximately 23 days. Moreover, one could note that good news in the stock market negatively affected the CAC40 index return volatility by 22% in the ‘Pre-Pandemic’ period and by 56.22% in the ‘In-Pandemic period’. In addition, it was found that bad news positively affected the CAC40 index return volatility by 46.90% in the ‘Pre-Pandemic’ period and by 4.81% in the ‘In-Pandemic’ period. When the CAC40 index return volatility permanence is examined, it is determined as 5 days in the Pre-Pandemic period and 15 days in the In-Pandemic period.

Diagnostic test statistics of EGARCH models are also included in Table 4. As a result of the predicted EGARCH models, the ARCH-LM test was conducted again to see if the ARCH effect in the return series disappeared. The ARCH-LM test statistic values calculated until the 10th lag are found to be statistically insignificant and the conditional variance effect in the series disappeared.

No autocorrelation problem was found when examining autocorrelation in the model series using the Ljung-Box Q^2 test until the 10th lag. The graphics of the return volatility series obtained as a result of EGARCH models are shown below (figures 5 to 8). By looking at the figures, it can be noted that the return volatility of major stock indexes has increased since the second month of the Covid-19 Pandemic period. At the start of the Covid-19 pandemic period, investors did or could not predict that the epidemic would spread rapidly and affect the markets. However, later, once the Covid-19 pandemic spread rapidly all over the world and uncertainty increased, volatility in the markets increased as a result.

[Insert Figure 5, 6, 7 and 8 Here]

7. Conclusion

As noted throughout history, disruptions of the norm by epidemics and economic crises have left an impact on community life. However, the disruptions caused by the Covid-19 pandemic seems to be much worse and far more devastating, maybe due to its global effect and the speed with which it is spreading, which might be a consequence of the new societal cultures and the ease of global travel.

Decreasing world trade and almost extinct tourism activities have minimized commercial activities in almost all countries. In this process, many businesses are closed and unemployment is on the rise. In the latest developments in the world economy, it has been determined that production has decreased and unemployment rates have increased in various countries and country groups. For example, it is stated that the US unemployment rate rose from 7.2% to 8.4%, and the unemployment rate in Japan rose from 5% to 6.1% (SBB, 2021). This affects financial markets expectations causing significant price fluctuations. Investors are facing ~~unprecedented and maybe irrational~~ volatility resulting from this new risk. Investors are facing volatility resulting from this new risk.

Our findings show that good news that flows to the markets during the 'Pre-Pandemic' period will reduce the volatility in the DJIA and the CAC40 indexes. However, during the 'In-Pandemic period', the good news, except in the case of the DJIA, created effects that reduce the volatility of the DAX, the FTSE100 and the CAC40 indexes. Moreover, although, volatility permanence decreased during the 'In-Pandemic' period except in the case of the DAX, volatility that occurs when bad news comes to the markets during this period is higher than in other periods. The reason for this may be the speed with which global news travels.

We also find that the Covid-19 pandemic increased the return volatility of all stock markets especially following the second month (February 2020) of the 'In-Pandemic' period. However, the volatility permanence during this period was short and the predicted EGARCH models show the presence of leverage in the returns. Also, during the 'In-Pandemic' period, good news has been observed to affect the stock index return volatility more than bad news except in the case of the DJIA index, with good news in the markets further reducing the stock return volatility of the DAX, the FTSE100 and the CAC40 during the 'In-Pandemic' period. The latter can be due to the positive effect of the mitigation measures taken by the economic administrators of the various countries and the rapid flow of information/news.

Although we were unable to find many studies to enable comparison may be due to these studies being at an early stage of the Covid-19 spread, our findings confirm and can be corroborated to the findings by Albulescu (2020a), Fernandes (2020), Ramelli and Wagner (2020b) and Zeren and Hızarcı (2020). However, we feel that it is important at this stage to provide some insight for investors trading in the financial markets, risk managers, actuaries, policymakers and portfolio managers to see the volatility change during this pandemic period and the volatility response of the market following news on the pandemic. The findings have also important implications for policymakers, academics and other interested people and institutions.

Conflict of Interest:

We declare no conflict of interest

Acknowledgements:

We declare no acknowledgements are applicable

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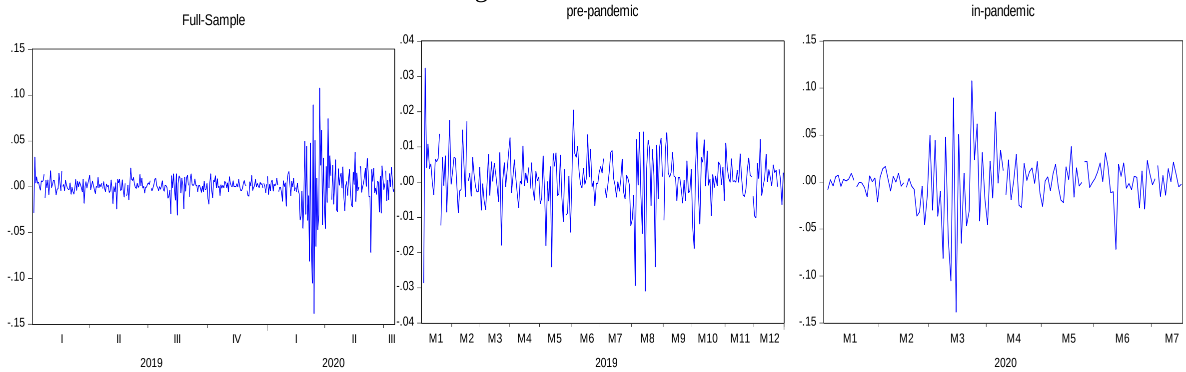
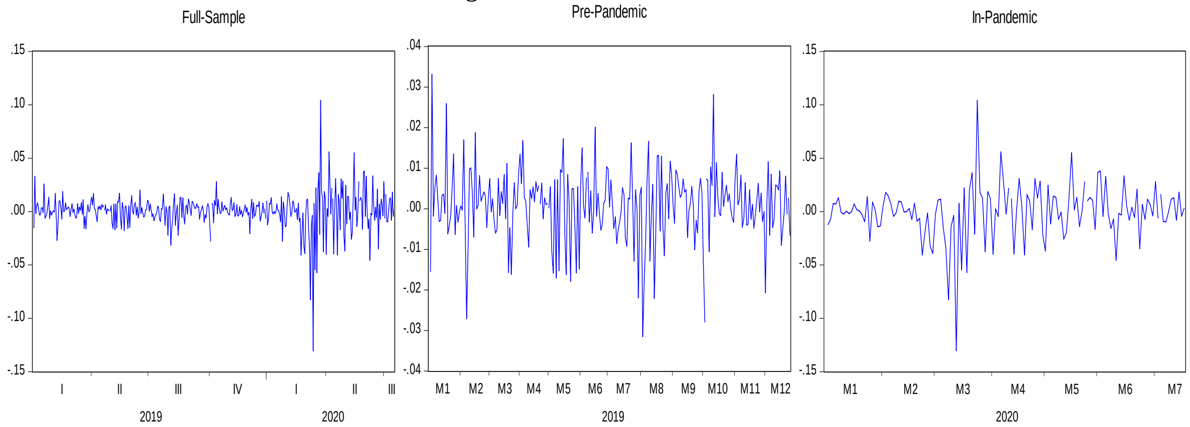
Figures and Tables

Figure 1. Series of DJI return



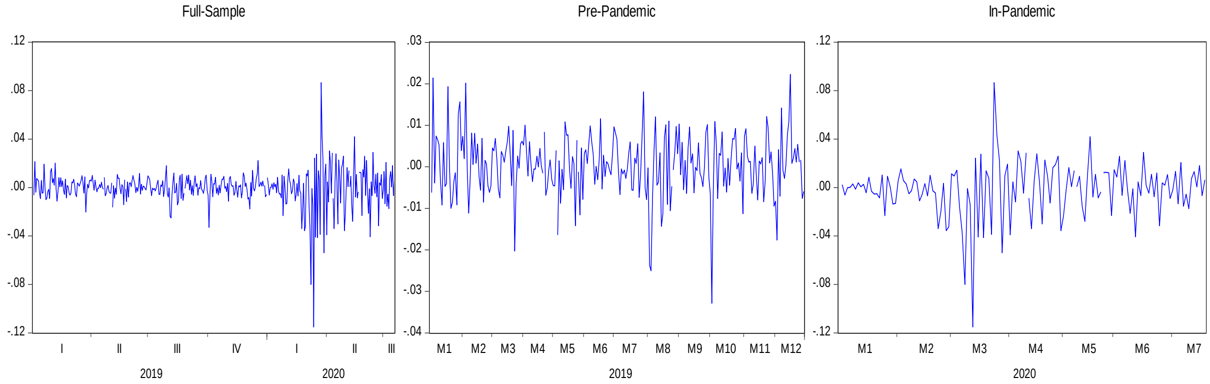
Source: Authors' Compilation

Figure 2. Series of DAX return



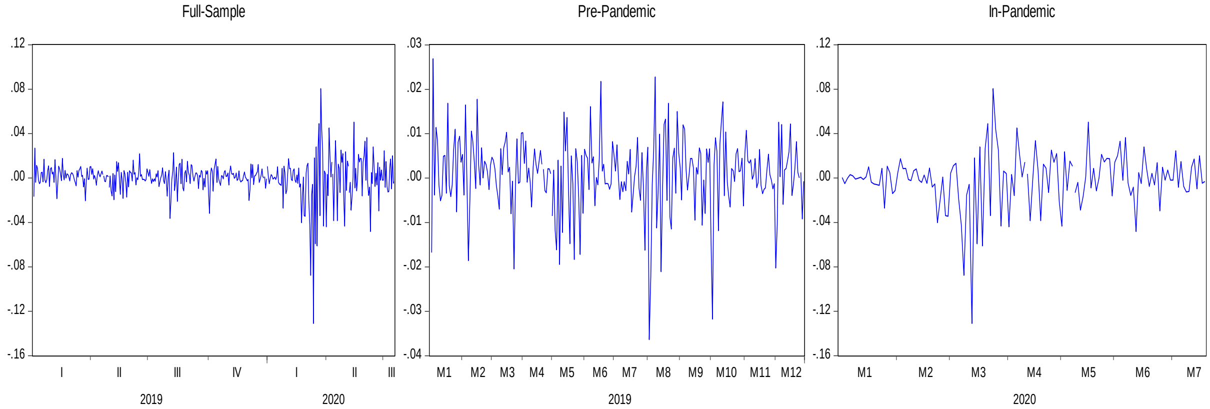
Source: Authors' Compilation

Figure 3. Series of FTSE100 return



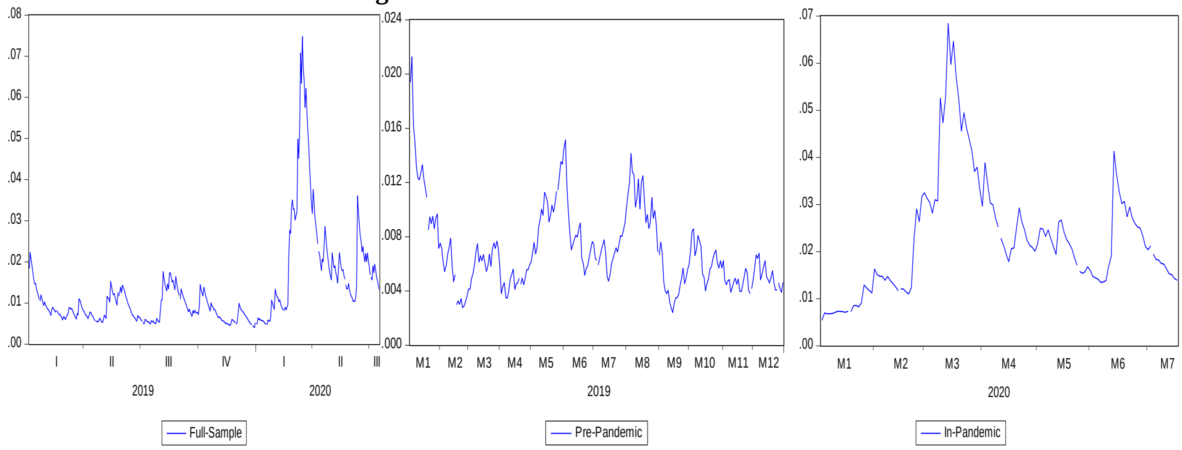
Source: Authors' Compilation

Figure 4. Series of CAC40 return



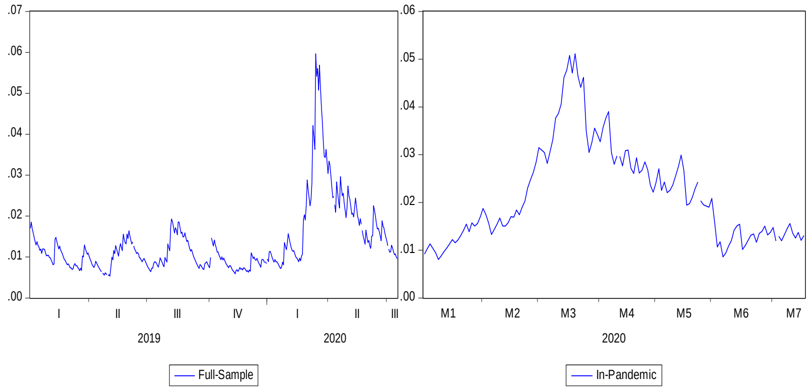
Source: Authors' Compilation

Figure 5: DJIA Conditional Standard Deviation



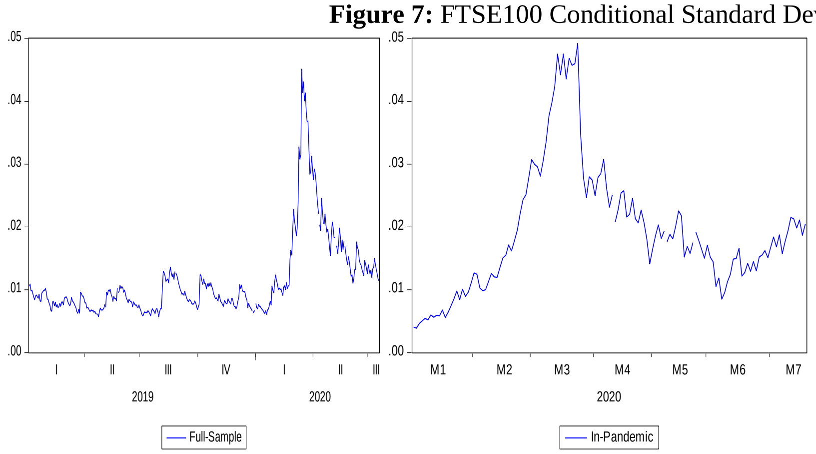
Source: Authors' Compilation

Figure 6: DAX Conditional Standard Deviation



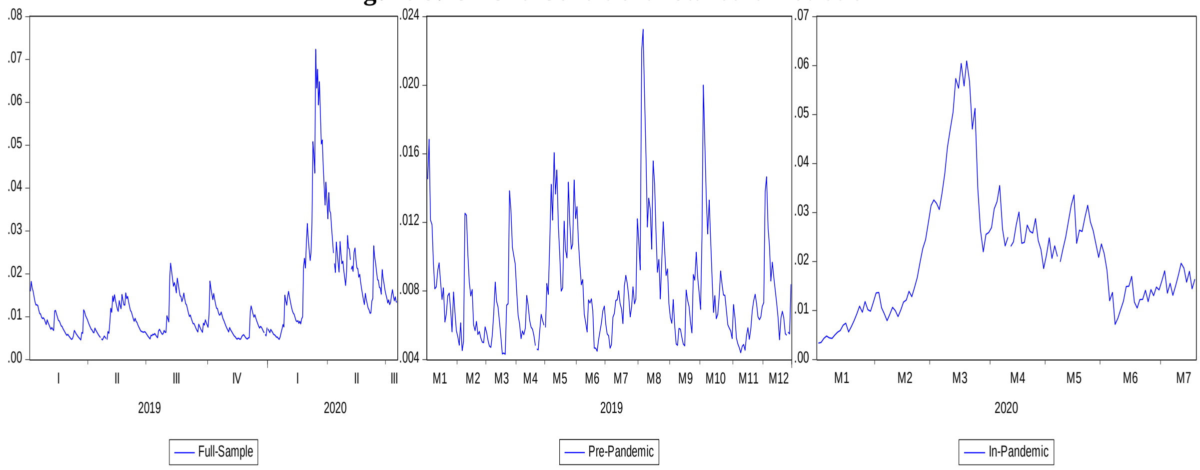
Source: Authors' Compilation

Figure 7: FTSE100 Conditional Standard Deviation



Source: Authors' Compilation

Figure 8: CAC40 Conditional Standard Deviation



Source: Authors' Compilation

Table 1: Descriptive Statistics

Index		Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP
DJIA	Full-sample	-0.0003	0.0190	-1.0107	17.7376	5577.442***	-6.5061***	-26.2288***
	Pre-Pandemic	0.0008	0.0078	-0.6639	6.2452	128.582***	-18.2644***	-18.1355***
	In-Pandemic	-0.0005	0.0303	-0.6081	7.7544	136.478***	-7.6043***	-15.9014***
DAX	Full-sample	0.0005	0.0167	-1.1438	17.8569	3653.071***	-19.6212***	-19.8595***
	Pre-Pandemic	0.0009	0.0088	-0.3551	4.9097	43.2445***	-15.8751***	-15.8821***

	In-Pandemic	-0.0003	0.0256	-0.8085	9.1539	231.106***	-11.5472***	-11.6906***
FTSE100	Full-sample	-0.0001	0.0147	-1.4533	17.4323	3522.064***	-6.7130***	-20.1527***
	Pre-Pandemic	0.0004	0.0074	-0.4385	5.1494	56.592***	-13.8479***	-13.7254***
	In-Pandemic	-0.0013	0.0228	-0.9607	8.4869	192.9337***	-12.2629***	-12.2475***
CAC40	Full-sample	-0.0001	0.0164	-1.7575	17.3637	3580.785***	-6.1577***	-20.0508***
	Pre-Pandemic	0.0009	0.0083	-0.7382	5.5685	92.894***	-11.8731***	-15.5502***
	In-Pandemic	-0.0012	0.0252	-1.1779	8.4933	205.4286***	-11.8166***	-11.9299***

*** indicate respectively statistical significance at the 1 percent levels.
Source: Authors' compilation

Table 2. ARMA Models

	DJI		
	Full-sample	**Pre-Pandemic**	**In-Pandemic**
	ARMA(2,2)	***ARMA(3,3)***	***ARMA(3,1)***
AIC	-5.301545	-6.853582	-4.363217
SIC	-5.240292	-6.755263	-4.234717
Log Likelihood	1034.500	867.1246	302.6987
$Q^2(10)$	398.44 (0.000)	30.240(0.001)	87.265 (0.000)
ARCH LM(10)	19.18651 (0.000)	3.970879(0.001)	5.085358 (0.000)
	DAX		
	Full-sample	**Pre-Pandemic**	**In-Pandemic**
	ARMA(3,2)	***ARMA(0,0)***	***ARMA(3,1)***
AIC	-5.376393	-6.615534	-4.513560
SIC	-5.304932	-6.601448	-4.385677
Log Likelihood	1050.020	827.9417	315.1788
$Q^2(10)$	127.68 (0.000)	**9.5287(0.483)**	37.569 (0.000)
ARCH LM(10)	12.55235(0.000)	**1.229649(0.2729)**	4.226727 (0.0001)
	FTSE100		
	Full-sample	**Pre-Pandemic**	**In-Pandemic**
	ARMA(3,3)	***ARMA(2,1)***	***ARMA(0,0)***
AIC	-5.681309	-6.971785	-4.713642
SIC	-5.599953	-6.901757	-4.692328
Log Likelihood	1115.855	883.4450	323.8845
$Q^2(10)$	144.67(0.000)	**4.8927(0.898)**	41.092 (0.000)
ARCH LM(10)	12.26871(0.000)	**0.557445(0.8474)**	3.893741 (0.0001)
	CAC40		
	Full-sample	**Pre-Pandemic**	**In-Pandemic**
	ARMA(0,0)	***ARMA(0,0)***	***ARMA0,0)***
AIC	-5.378274	-6.725962	-4.511885
SIC	-5.368163	-6.712036	-4.490673
Log Likelihood	1057.831	855.1972	312.3201
$Q^2(10)$	193.55 (0.000)	21.823(0.016)	44.558 (0.000)
ARCH LM(10)	13.97479 (0.000)	1.888285(0.0476)	3.473857 (0.0005)

Source: Authors' Compilation

Table 3. Results for EGARCH Models

	DJIA		
	Full-sample	**Pre-Pandemic**	**In-Pandemic**

	EGARCH(1,1)		EGARCH(1,1)		EGARCH(1,1)	
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
c	-0.402470	0.0032	-0.245537	0.0000	-0.668359	0.0149
α_1	0.247458	0.0003	-0.173856	0.0000	0.281471	0.0322
γ	-0.175714	0.0000	-0.276640	0.0000	-0.178767	0.0633
β_1	0.975827	0.0000	0.964622	0.0000	0.939683	0.0000
Model İstatistic						
AIC	-6.274387		-7.226801		-4.970345	
SIC	-6.223343		-7.156573		-4.863262	
Log Likelihood	1222.231		911.9635		342.9835	
Q^2(10)	10.404 (0.406)		10,498(0.398)		3.3034 (0.973)	
ARCH LM(10)	0.926935 (0.5082)		1,113746(0.3526)		0.290503 (0.9822)	
	DAX					
	Full-sample EGARCH(1,1)		**Pre-Pandemic**		**In-Pandemic EGARCH(1,1)**	
	Coefficient	p-Value			Coefficient	p-Value
c	-0.310972	0.0003	There is no heteroskedasticity		-0.040173	0.0729
α_1	0.151184	0.0002			-0.168013	0.0025
γ	-0.181040	0.0000			-0.226907	0.0002
β_1	0.978318	0.0000			0.978807	0.0000
Model İstatistic						
AIC	-5.992638		There is no heteroskedasticity		-5.050382	
SIC	-5.951803				-4.965127	
Log Likelihood	1166.572				349.9512	
Q^2(10)	5.2499 (0.874)				16.134 (0.096)	
ARCH LM(10)	0.517790 (0.8776)				1.226430 (0.2815)	
	FTSE100					
	Full-sample EGARCH(1,1)		**Pre-Pandemic**		**In-Pandemic EGARCH(1,1)**	
	Coefficient	p-Value			Coefficient	p-Value
c	-0.238076	0.0001	There is no heteroskedasticity		-0.158380	0.0017
α_1	0.077956	0.0030			-0.196420	0.0030
γ	-0.161550	0.0000			-0.244156	0.0000
β_1	0.980482	0.0000			0.958521	0.0000
Model İstatistic						
AIC	-6.286375		There is no heteroskedasticity		-5.268798	
SIC	-6.245696				-5.183543	
Log Likelihood	1229.843				364.9126	
Q^2(10)	5.7663 (0.835)				13.327 (0.206)	
ARCH LM(10)	0.567411 (0.8405)				1.053565 (0.4039)	
	CAC40					
	Full-sample EGARCH(1,1)		**Pre-Pandemic EGARCH(1,1)**		**In-Pandemic EGARCH(1,1)**	
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
c	-0.421153	0.0020	-1.391017	0.0002	-0.136783	0.0000
α_1	0.211022	0.0007	0.123073	0.0378	-0.257051	0.0000
γ	-0.205228	0.0000	-0.345931	0.0000	-0.305154	0.0000
β_1	0.970653	0.0000	0.868100	0.0000	0.955040	0.0000
Model İstatistic						
AIC	-6.237952		-6.889834		-5.163292	
SIC	-6.187394		-6.834128		-5.078444	
Log Likelihood	1230.758		879.0089		360.2672	
Q^2(10)	4.2291 (0.936)		5.1303 (0.882)		12.616 (0.246)	
ARCH LM(10)	0.410347 (0.9415)		0.514933 (0.8788)		1.159263 (0.3253)	

Source: Authors' Compilation

Table 4. Volatility Status of Stock Index Returns in All Periods

Index		**The Effect of Good News on Volatility (α + γ)**	**The Effect of Bad News on Volatility (α - γ)**	**Volatility Persistence (HL)**
DJIA	Full-sample	0.0714	0.4232	28.33 days
	Pre-Pandemic	-0.4505	0.1027	19.24 days
	In-Pandemic	0.1027	0.4602	11.14 days

DAX	Full-sample	-0.0298	0.3322	31.62 days
	Pre-Pandemic	There is no heteroskedasticity		
	In-Pandemic	-0.3949	0.0589	32.35 days
FTSE100	Full-sample	-0.0836	0.2395	35.17 days
	Pre-Pandemic	There is no heteroskedasticity		
	In-Pandemic	-0.4406	0.0477	16.36 days
CAC40	Full-sample	0.0058	0.4163	23.27 days
	Pre-Pandemic	-0.2229	0.4690	4.90 days
	In-Pandemic	-0.5622	0.0481	15.06 days

Source: Authors' Compilation