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A cross-country study of stock markets volatility before and during the Covid-19 pandemic

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Abstract

At the end of 2019, the SARS-CoV virus began to spread thereby forcing each country to establish their own systems of restrictions and controls to mitigate infections. This resulted in decline global trade, disruption in supply chain and substantial drop in stock prices. This research paper examines the effects of Covid-19 on major global stock indexes, for example, Nasdaq 100, FTSE 100, CAC 40, DAX 30, and Nikkei 225. The data analysis focuses on the Covid-19 period from 2020 to 2021, and before Covid-19 period starting from 2015 to 2019. GARCH and ARCH models have applied to analyze data.

Introduction

The beginning 2020s was marked by an unprecedented health emergency and a crisis due to the Covid-19 pandemic. The way to face the named emergency in each country has depended on the cultural, social, geographical, economic environment and political factors. In January 2020, the world began to know about covid-19, the rapid spread of the virus and the increasing number of confirmed cases caused rapid reactions from the Chinese government. As time passed, and the virus crossed land and sea borders, the World Health Organization (WHO) officially declared that the Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) outbreak as a global pandemic on March 11, 2020 (Zhang, Hu, & Ji, 2020).

Analyzing and explaining the effects of the pandemic on the economy is a very extensive topic, there are various components to be considered. Undoubtedly, one of the components that has been highly exposed during the pandemic, are the stock markets. "Compared to other macroeconomic indicators such as unemployment rates or GDP, stock prices are constantly available and adjusted, making it possible to analyze the effects of a crisis period, even before and during the different phases of the crisis" (Wielechowski & Czech, 2021, pp. 1–2).

Furthermore, considering the variation of response measures adopted by governments around the world and sheer scale of the pandemic, the stock markets around the world experienced unprecedented uncertainties and volatilities. These uncertainties and volatilities were markedly different from the *usual* fluctuation caused by expected and unexpected developments related to political events, natural calamities, and socio-economic determinants, among others (Wielechowski & Czech, 2021). In the wake of Covid-19, global stock markets have been showing the patterns of disruptions, which are markedly different from the ones observed in the previous global socio-economic crises. On the other hand, stock markets around the world have not been homogeneous in terms of absorption of the Covid-19 effects. Following the WHO's official announcement about the global pandemic, financial markets around the world began to fall. The strongest stock market reaction was seen in the early phase of the pandemic. On Monday, March 16, 2020, the US indices recorded shocking declines, the Dow Jones industrial average fell by almost 13%, while the S&P 500 fell by almost 12%. Similarly, European markets recorded substantial losses, with the pan-European STOXX 600 went down by 8.7%; whereas Germany's benchmark DAX30, CAC40, and FTSE100 declined by 7.1%, 8.4%, 4%, respectively. Additionally, the markets in the Asian giants were also affected, with Shanghai falling by 3.4%, the Shenzhen index registering a loss of 5.34% and Hong Kong's Hang Seng falling by more than 4% (DW Journal, 2020).

The key motivation of the current study is to explore the effects of such a high scale disruption phenomenon on the global financial markets, especially those which are sudden, abrupt, and massive, for example various types of global economic or environment crises. Lately, such global crises have become more frequent, and extensive. Such developments have challenged many researchers to explore causes, explain the consequences, and lay the foundations for future research including the development of different techniques and methodologies.

Even though the crisis generated by Covid-19 is still present, access to information and the evident effects on the world economy have already put researchers and scientists to work. Some authors have explained in a general way the effects on the global economy, others have delved into explaining the reaction of certain sectors. Those interested in macroeconomic determinants have been analyzing it, for example, from the monetary, and fiscal mechanism, while others have been exploring the association between global crises and stock markets' reactions.

This research has the primary objective of explaining and comparing the behavior of the five stock indexes:

Nasdaq 100, FTSE 100, CAC 40, DAX 30 and Nikkei225; during the period defined as *Pre-Covid-19 Period*. The *Pre-Covid-19 Period* is taken from January 2, 2015 to December 30, 2019, while *Covid-19-Period*, which basically represents *'during Covid-19'* period, is taken from January 2, 2020 to December 30, 2021. The analysis is primarily based on the daily return and volatility of each index. The key finding of the study are-1. rapid and strong decline in the indices in March 2020 was offset by a rapid recovery; 2. volatility of the indices stabilized in the first 5 months of the *Covid-19-Period* despite high volatilities, nonetheless, the volatility also decreased significantly at the end of 2020. It is expected that the results obtained in this detailed investigation can explain the response and changes in the financial markets in 5 of the world's largest economies, during the Covid-19 period. Likewise, the findings can serve as a basis for future research on the same topic at the country, sector, industry, or firm level.

Literature review

The cross-sectional study in this text focuses on the analysis of the stock indices of the 5 stock indexes in question, these indices are made up of a set of values listed on the corresponding stock exchange/index. These securities, commonly known as shares, are considered financial assets, since their value or benefit is an obligation of future money; that is, the possession of a share brings a benefit to the investor, either by receiving dividends from the company that issues the shares.

If the issue of a dividend is not considered, the benefit for the investor lies in the retention of the share for an indefinite period of time, which in turn generates a simple rate of return. These rates measure the degree to which a gain or loss has occurred over the period of time the stock was held. The calculation of this simple rate of return (R_t) is calculated from the following formula, where the P_t factor represents the actual price of the stock and P_{t-1} reflects de previous price of the stock:

$$R_t = (P_t - P_{t-1} / P_{t-1})$$

Since the original objective of this text is to study the behavior of stock market indices based on the behavior of individual assets before and during Covid-19 Pandemic, evaluating the performance of a stock goes beyond simply looking at the benefits of an asset price change from day to day.

Over time, several analytical models have been developed that allow investors and researchers to evaluate the behavior of both an individual stock and the behavior of an entire financial market over a predetermined period. The following sections show the findings of information about the models used in this present investigation.

As the pandemic has developed, the volatility of financial markets has increased substantially, and thereby reducing the investors' confidence in the stock markets. Shu (2010) has studied how investors' sentiments affect financial market behavior, intrinsic as well as extrinsic values assets, and expected returns. When the market is trending upwards and less risk is perceived, the investors behave more optimistically. Whereas when the market is trending down, investor sentiment becomes relatively pessimistic, and investors will tend to wait and watch for the market until a revival begins.

ARCH and GARCH Models

Volatility is a factor to consider when studying the behavior of financial securities. Volatility is defined as the conditional variance of an underlying financial series, for example a series of yields. In general, volatility is not constant and, consequently, traditional time series models that assume homoscedastic variance are not suitable for modeling financial time series.

In the financial series there are long periods of high volatility followed by periods of low volatility, which indicates the presence of heteroscedasticity and agglomeration. Furthermore, large changes in volatility are followed by large changes while small changes follow small changes in volatility.

If this change in variance can be correlated over time, then it can be modeled using an autoregressive process, such as the ARCH or GARCH model. Engle (1982) introduced a new class of stochastic processes called ARCH models, in which the conditional variance of past information is not constant and depends on the square of past innovations. Subsequently, Bollerslev (1986) generalized the ARCH models by proposing GARCH models in which the conditional variance depends not only on the squares of the disturbances, as in Engle, but also on the conditional variances of previous periods.

Some authors have recorded increases in volatility during the period of the Covid-19 pandemic. Sharma (2020) examines the similarity in volatility in Asian stock markets observed before and during the pre-COVID-19 period. Using daily data from Asian stock markets and an autoregressive model, the study finds that regional-level aggregate market volatility has a significant effect on country-level market volatility in 5 of the Asian economies.

On the other hand, Yousef (2020), analyzes the impact of the Covid-19 cases on the returns of the main G7 indices, also examines the stock market volatility for the seven indices using the regression models. The studied found that ARCH effects are highly significant for all G7 indices, indicating the presence of volatility conglomeration in the data series. The results of the GARCH and GJR-GARCH models reveal that the COVID-19 coefficient has a significant positive impact on the conditional variance of the G7 indices, implying that the coronavirus has increased stock market volatility in these countries.

Research Framework

The response of 5 stock indexes around the world has been explored during the Pre Covid 2019 period and during the Covid-19 period. Therefore, the daily returns of the Nasdaq 100, FTSE 100, CAC 40, DAX 30 and Nikkei 225 indices have been calculated for the two periods to be studied and compared. Each return was obtained based on the daily closing price of each asset, this information was extracted from the website "investing.com". The following section explains the methodoly use to calculate the volatility of the indices by calculating the variance conditional on the ARCH and GARCH models.

Methodology

Classical regression models assume that in linear series, the variance of the errors is constant, or homoscedastic. ARCH model, on the other hand, assume that the variance is not constant, so that this model allows to explain and to model the agglomeration or clustering of volatility that occurs in series of financial assets, which are characterized by being non-linear series. In this paper, the series to be studied are the returns on the financial assets in question. Usually, the non-constant variance of a financial asset is referred to as conditional variance and can be expressed as σ^2_t:

$$\sigma^2_t = var(u_t \mid u_{t-1}, u_{t-2}, \ldots, u_{t-q}) = E[u^2_t \mid u_{t-1}, u_{t-2}, \ldots, u_{t-q}]$$

According to the equation, above, the conditional variance of a random variable can be called equal to the conditional variance of the squared residual. In ARCH model, autocorrelation in volatility is modeled by allowing the conditional variance of the error term, σ2t, to depend on the prior value of the squared error:

$$\sigma^2_{t=} \omega + \alpha_1 u^2_{t-1}$$

where the perimeter "ω" represents the variance of an initial time as a constant term; the coefficient "α_1" represents the impact of the information of the previous variance; and u^2_{t-1} represents the prior value of the squared error. It is possible that the ARCH model can be extended to the general case, where the error variance depends on "q" lags of the squared errors:

$$\sigma^2_{t=} \omega + \alpha_1 u^2_{t-1} + \alpha_2 u^2_{t-2} + \ldots + \alpha_q u^2_{q-1}$$

Within the ARCH model there are limitations, such as the fact that the value of (q), that is, the number of lags of the squared error that is required to capture all the dependency on the conditional variance, can become very large and it would result in a conditional variance model that is not phlegmatic. Likewise, many lags "q" can cause one of the coefficients to become negative and impossible to interpret. Furthermore, Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model is an extension of the ARCH model with the difference that σ^2t becomes recursive, it finds the average medium-term volatility by means of an autoregression that depends on the sum of the lagged errors and the sum of the lagged variances. GARCH model is more phlegmatic and avoids overfitting, thus allowing the conditional variance to be dependent on its own lags and decreasing the possibility of negative results.

$$\sigma^2_{t=} \omega + \alpha_1 u^2_{t-1} + \beta_1 \sigma^2_{p-1}$$

In the prevoius conditional adjusted variance equation, the parameter ω represents the variance of an initial time period as a constant term. The coefficient α1 accounts for the impact of the prior variance information proxied by; u^2_{t-1} represents the prior value of the squared error; the coefficient β_1 explains the model-adjusted variance of the previous period's model; and σ^2_{p-1} means the historical squared lagged variance in a period where the parameter $_p$ is the weight for each distance between $_t$ observations.

Descriptive Analysis Pre-Covid19 Period

In our descriptive analysis we built graphs that compare the realized volatility, the conditional volatility from the ARCH model and the conditional volatility from the GARCH model. It is important to mention that this research considers realized volatility simply as the measure of daily changes in the price of a security during a particular period.

Starting with the analysis of the US index (Figure 1), according to the ARCH model, the volatility of the Nasdaq from January 2015 to December 20219 is explained by 33.61% of the variance of a previous day. While the GARCH model explains that the volatility of the Nasdaq 100 is explained in 23.7% by the conditional variance of a previous day and in 60.18% by the adjusted variance of a period. Almost all the volatility from ARCH has slightly higher peaks than GARCH volatility. On August 26, 2015, there is a high peak, where the realized volatility reached 4.31 followed by the GARCH volatility of 1.72% and the ARCH conditional volatility of 1.65%. In the following months, the volatility had highs and lows, staying in a range of 0.12% to 4.22% of actual volatility and from 0.9% to 3% of conditioned volatility. In December 2016, a peak reached a 6,13% in realized volatility, but conditional volatility remained at 1.18% in GARCH and 0.91% in ARCH, which indicates that the variance of a previous day and the adjusted variability of the period does not have as much impact on the volatility of the index.

Similarly, to the British index (Figure 2), the daily variances of the FTSE 100 index indicate that the moment of greatest volatility occurred peculiarly on August 24, 2015, where the realized volatility reached 4.70%, followed by the GARCH volatility of 2,30%. and ARCH volatility of 1.80% according to the ARCH model. In the following months, there are peaks in October 2016 and notable increases in January 2016, reaching levels of 3.55%. However, in time, the FTSE 100 is less volatile during the year 2017 and is more volatility from December 2018 October 2019. According to the GARCH model, 28.13% of the volatility of the FTSE 100 is explained by the conditional variance of a previous day and 61.29% by the adjusted variance of a period. And unlike the Nasdaq index, the difference between the ARCH and GARCH volatility varies, and the conditional variance has slightly more impact on the volatility of the British index.

Figure 1. Nasdaq 100 Volatility 2015-2019

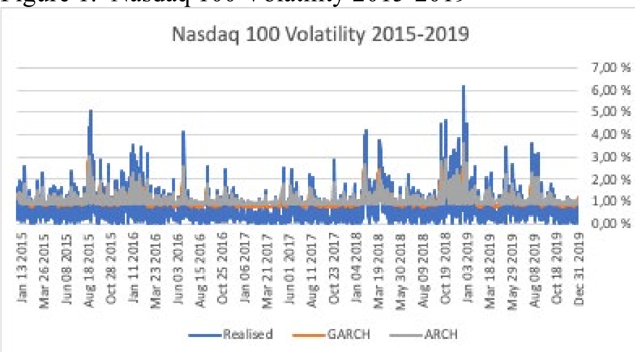
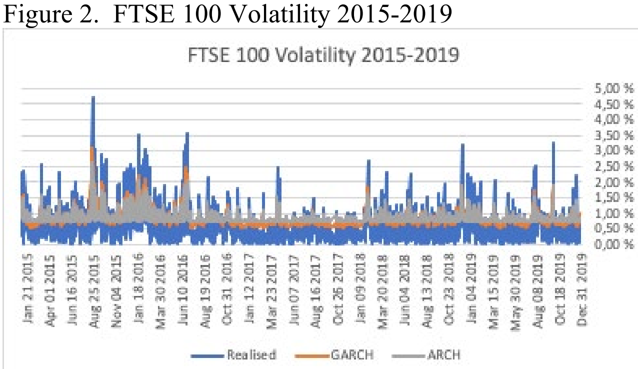


Figure 2. FTSE 100 Volatility 2015-2019



On the other hand, the European CAC 40 (Table 3) and DAX 30 (Figure 4) indices present similarities in the behavior of their volatility. June 24, 2016, is the day with the highest volatility peak, the French index registering 8.06% of the realized volatility and the German index registered a value of 6.83%, the conditional volatilities of the CAC 40 remained 1.95% GARCH and 1.81% ARCH and while the conditional volatilities of DAX 30 remained at 1.79% and 1.71%. In contrast, the CAC 40 index presents in the ARCH model that 28.14% of the volatility is influenced by the variance of a previous day, the coefficient is higher than that of the DAX, which barely exceeds 20.7%. In the GARCH model, the coefficient of conditional variance of the previous day is greater in the DAX 30 index than in the CAC 40 index, but the coefficient of the adjusted variance of the period is less by a difference of 413 basis points. It is important to mention that compared to previous indices, these indices present fewer high peaks.

Regarding the Nikkei 225 index (Figure 5), periods of high volatility are reflected in conglomerations starting in September 2015. Likewise, the European indices, a high peak is seen on June 24 that raised to 7.9% of the realized volatility and 1.5% of the conditional volatility in both Autoregressive models. Throughout the year 2017, the volatility of the Japanese index is low, and even the conditional volatility in GARCH and ARCH becomes higher than the realized volatility, remaining in ranges below 1.5%. In 2018, there were increases but not greater than 5% in realized volatility and 3% in conditional volatility in both models.

Figure 3. CAC 40 Volatility 2015-2019

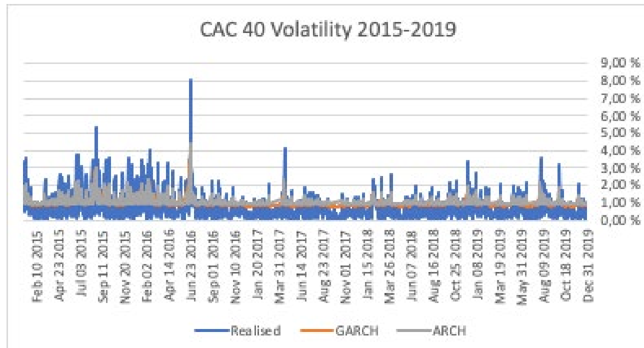


Figure 4. DAX 30 Volatility 2015-2019

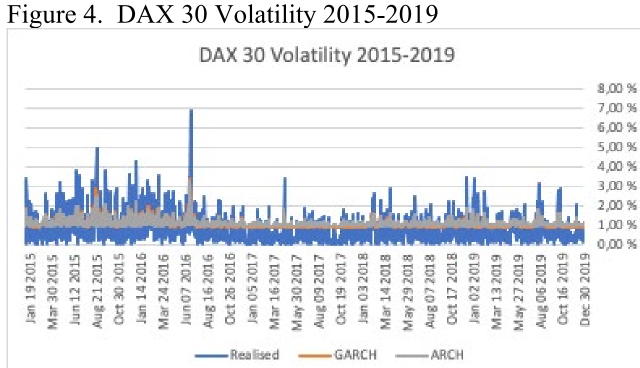
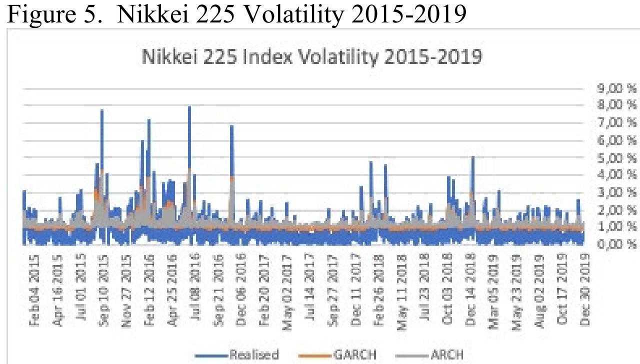


Figure 5. Nikkei 225 Volatility 2015-2019



Descriptive Analysis during Covid-19 period

In this section, some of the findings of the reactions of the indices to be studied during the Covid-19 period from January 2020 to December 2021 are interpreted. From an overview, the parameters of the realized and the conditional volatility in the ARCH and GARCH models is slightly higher compared to the *Pre-Covid period.* In addition, the difference between the parameters of each volatility is smaller, and at times, the conditional volatility in both models becomes greater than the realized volatility.

The ARCH and GARCH parameters of the Nasdaq 100 index (Table 6) during the Covid-19 period do not differ greatly from the parameters of the previous period; according to the GARCH model, the volatility of the Nasdaq 100 is explained in 25.6% by the conditional variance of a previous day and 65.07% in by the adjusted conditional variance of the period. The Nasdaq 100 index presents the greatest increase in volatility on March 16, 2016, the same day that the largest falls in the stock markets were presented after the announcement of the official declaration of Covid-19 as a global pandemic by the World Health Organization on March 11, 2020. The realized volatility reached a value of 12.23%, being the highest value reached in the analysis of all the indices in both periods. That same day, the conditional volatilities in the ARCH model and the adjusted volatility of the GARCH model remain at 4.21% and 4.30% respectively, however, days before the falls, the conditional volatilities are around 6% to 8%. In the remaining months of 2020, the index presents peaks that do not exceed 5.4% and particularly as of December 2020, the conditional volatility of the ARCH model exceeds the realized volatility and adjusted volatility of the GARCH model; One factor to consider in this finding could be the announcement of the authorization by the Food and Drug Administration (FDA) of the Pfizer-BioNTech vaccine against COVID-19 in people over 16 years of age in the US on December 11, 2020.

The British index (Figure 7) registers its highest point of volatility one day before that of the US index, with realized volatility reaching 10.86%, and conditional volatilities reaching 2.04% and 2.81% in the ARCH and GARCH models, respectively. The behavior of volatility in the following months is similar to that of the American index, although fewer conglomerations are observed. And in relation to the parameters of the ARCH model, the volatility of the FTSE 100 depends 180 base points more on the conditioned variance in the Covid-19 period than during previous years; on the other hand, the GARCH model shows parameters greater than the previous period, volatility is explained at 41.04% by the conditional variance and 48.3% by the adjusted conditional variance.

Figure 6. Nasdaq 100 Volatility 2020-2021

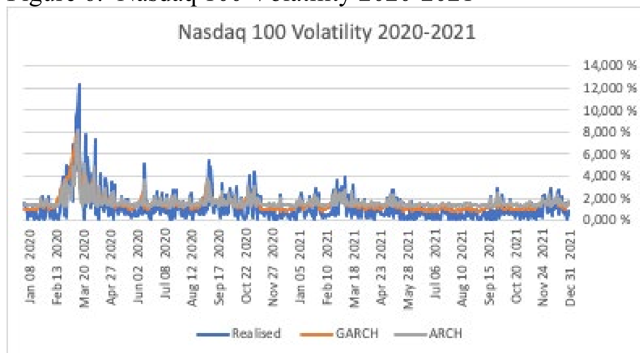
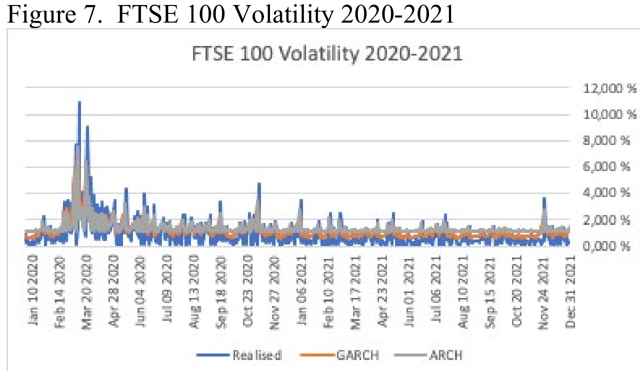


Figure 7. FTSE 100 Volatility 2020-2021



DAX 30 (Figure 9) also features its highest point of volatility realized on the same day as the French index, with a difference of 94 basis points. Unlike the CAC 40 index, particularly the conditional volatility of the German index, it climbs back to 7.32% in the ARCH model on March 23, 2020, and although the next day it drops 5,497 basis points, the realized volatility rises to 10 .9%. From November 10, 2020 to November 25, 2021, the realized volatility does not exceed 5% and the conditional volatility does not exceed 4%. Regarding the coefficients in the autoregressive models, the ARCH model shows that 42.06% of the volatility is explained by the prior variance, while the GARCH model explains that 14.6% of the volatility is explained by the prior variance and 77.67% for the adjusted variance of the period.

Figure 8. CAC 40 Volatility 2020-2021

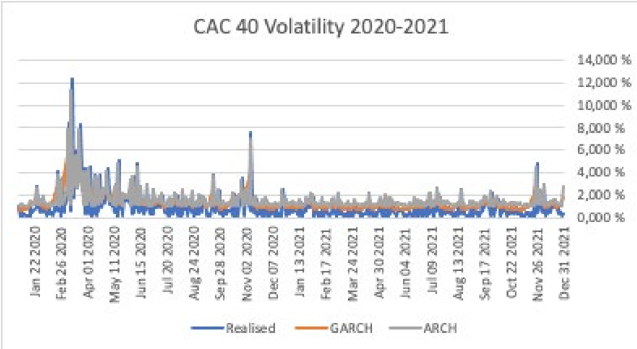


Figure 9. DAX 30 Volatility 2020-2021

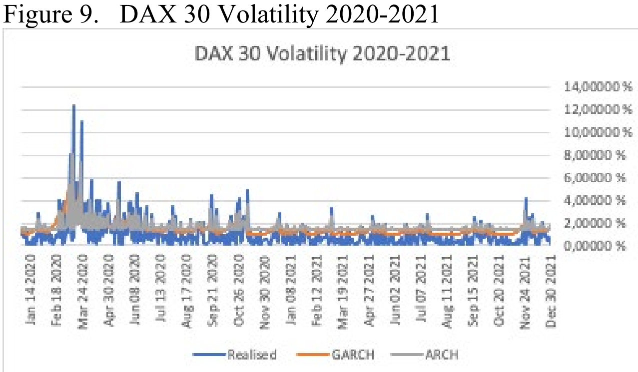
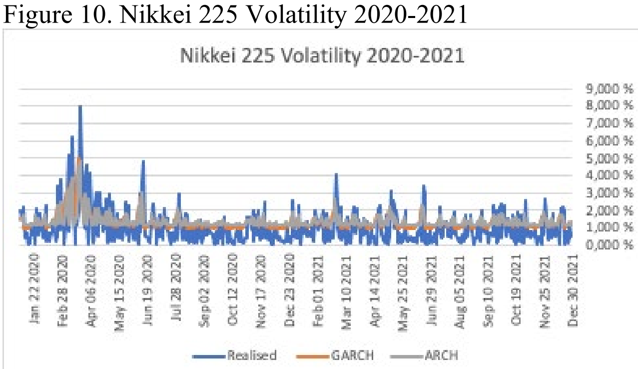


Figure 10. Nikkei 225 Volatility 2020-2021



Finally, the Japanese index (Figure 10) presents conglomerations of high volatility at the beginning of March, however, it is not until March 23, 2020, when the conditioned volatility in the ARCH model exceeds 5%. Unlike western indices, the realized volatility of the Nikkei 225 only increases to 7.9%. There are fluctuations in the following months, but the highest peak of realized volatility barely reaches 4%. It can be considered that the Nikkei has lower volatility ranges compared to the other indices, due to the fact that the Asian index is made up of more individual stocks, which diversifies and stabilizes the daily rate of return of the index and therefore the volatility during any period. Moreover, the ARCH model reflects that 34.8% of the volatility is explained by the prior variance, while the GARCH model reduces this postulate to 27.9% and argues that the volatility depends 45.8% on the adjusted variance of the period, as can be seen, these coefficients are lower than the coefficients of the Western indices during the Covid-19 Period.

Conclusion

It is proven that stock markets are inherent to unexpected events such as the spread of a virus globally. And it is that although the Covid-19 had its origin in China at the end of 2019, once the virus began to spread rapidly, the countries began to execute harsh restrictions that had a direct impact on companies, world trade and therefore in stock indices. Although the volatility of the stock markets in the years prior to the Pandemic was not homogeneous and the ranges were lower; additionally, the ARCH and GARCH models revealed that the volatility is influenced by the prior variance and the conditional variance. High volatility periods were also shown to differ between indices during the Pre-Covid-19 period.

The ARCH and GARCH models during the Covid-19 Period show higher parameters, so the volatility is much more affected by the prior variance and the conditional variance than in the previous period, and even the conditional volatility becomes higher than the realized volatility in days prior to the crash of the stock markets. Unlike the previous period, the indices behave in a similar way with slight differences in the levels of volatility reached. rapid and strong decline in the indices in March 2020 was offset by a rapid recovery; 2. volatility of the indices stabilized in the first 5 months of the *Covid-19-Period* despite high volatilities, nonetheless, the volatility also decreased significantly at the end of 2020.

This general study of 5 of the most important stock indices in the world economy, can be used as references for future research on the same topic. Also, the findings can be complemented with future individual research on each index, which allows explaining the behavior of the assets. and make conclusions by sector or industry, or even make comparisons with the actual return, expected return, risk and others. There are multiple possible studies to be carried out, and although this crisis will not be the last to impact the world economy, there will be other events that will give sufficient reason to investigate and interpret.

References

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Deutsche Welle (www.dw.com). (2020, March 16). Stock markets plunge on coronavirus fears. *DW.COM*. https://www.dw.com/en/stock-markets-plunge-on-coronavirus-fears/a-52790114

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, 50(4), 987. https://doi.org/10.2307/1912773

Office of the Commissioner. (2021, August 23). FDA Approves First COVID-19 Vaccine. U.S. Food and Drug Administration. Retrieved April 30, 2022, from https://www.fda.gov/news-events/press-announcements/fda-approves-first-covid-19-vaccine

Sharma, S. S. (2020). A Note on the Asian Market Volatility During the COVID-19 Pandemic. Asian Economics Letters, 1(2). https://doi.org/10.46557/001c.17661

Shu, H. C. (2010). Investor mood and financial markets. Journal of Economic Behavior & Organization, 76(2), 267–282. https://doi.org/10.1016/j.jebo.2010.06.004

Wielechowski, M., & Czech, K. (2021). Companies' Stock Market Performance in the Time of COVID-19: Alternative Energy vs. Main Stock Market Sectors. Energies, 15(1), 106. https://doi.org/10.3390/en15010106

World Economic Forum. (2020, April 4). How does coronavirus affect the economy? Retrieved 14 March 2022, from https://www.weforum.org/agenda/2020/03/imf-economic-lessons-from-china-fight-against-coronavirus

Yousef, I. (2020, May). Spillover of COVID-19: Impact on Stock Market Volatility. ResearchGate GmbH. Retrieved March 20, 2022, from https://www.researchgate.net/publication/341134119_Spillover_of_COVID-19_Impact_on_Stock_Market_Volatility

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. Finance Research Letters, 36, 101528. https://doi.org/10.1016/j.frl.2020.101528