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A New Approach to Assess Stock Market Risk-return and Volatility in the Context of Covid-19-A Study of Multiple Stock Markets

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Description

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Abstract

The second decade of the 21st century was greeted with the rapid spread of the SARS-CoV virus. In March 2020, each country was forced to establish its own systems of restrictions and controls to mitigate contagion. This caused strong effects in the global economy, such as a substantial drop in stock prices. This unpredictable event caused abrupt and non-homogeneous changes in stock markets around the world at different stages of the so-called Covid-19 crisis, causing a state of alertness and concern among investors. This study examines the effects of Covid-19 on five major global stock indexes: Nasdaq 100, FTSE 100, CAC 40, DAX 30, and Nikkei 225. The data analysis focuses on the behavior of the mentioned indexes and thirty stocks listed in each index during the Covid-19 period from 2020 to 2021 and before the Covid-19 period from 2015 to 2019. This thesis is divided into two sections. The first section explains the mentioned assets' behavior based on their return and risk; the Capital asset pricing model (CAPM) and Jensen's Alpha are applied in this section; the synthesized results reflect that the rate of return of the indexes was not homogeneous between them and between the selected stocks during the Covid-19 period, there are variations between the realized rate of return and the expected rate of return, there is an increase in financial risk and insistent in most of the indexes due to an increase in the beta coefficient, however this change is not significant between the two study periods.
In the second section, the realized volatility, conditional volatility and conditional volatility are modeled and analyzed with the application of the Autoregressive models: ARCH and GARCH. The output indicated that unlike the period before Covid-19 pandemic, the indexes behaved in a similar way with slight differences, and they presented lower volatility ranges; a rapid and strong decline in the indexes in March 2020 was offset by a rapid recovery in the first 5 months of the Covid-19-Period; and the volatility is much more affected by the conditional variance and the conditional adjusted variance than in the previous period.

Keywords/tags (subjects)

Risk-return, CAPM, Jensen´s Alpha, volatility, ARCH, GARCH

Miscellaneous

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Contents

1 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).

The rapid spread of the Covid-19 disease and the drastic response measures adopted by governments in 2020 caused a biggest contraction in the economy since the 1930s. In fact, "The impact of the coronavirus disease is severe even compared to the Great Financial Crisis of 2007-08" **(**WEF, 2020, para.5). The pandemic interrupted the production and consumption chains in most countries, reducing global demand, and generating a drop in international trade. The generated serious consequences reflected in the economic and social levels in the countries, such as: the drop in the Gross Domestic Product (GDP) in practically all the world's economies; discrepancies in the balance of payments; rise in consumer price indexes; increases in unemployment rates; increases in the levels of poverty and inequality in various areas. According to the World Bank, (2021) , in terms of economic growth, the pandemic meant a global economic contraction in 2020 of 4,3%. This decline was slightly less severe than initially projected, mainly because the contraction in advanced economies was less pronounced than expected, and the recovery in China was faster than anticipated. The falls of important economies stand out, such as the United States (-3,6%), the Euro Zone (-7,4%), Japan (-5,3%), and China (+2%), being the latter one of the few countries that experienced a positive figure in the midst of the disease.

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 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 indexes 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 DAX 30, CAC 40, 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).

As the pandemic has developed, the volatility of financial markets has increased the uncertainty which reduced the confidence that investors usually have in the stock market. A significant analysis and discussion on how investors' moods affect financial market behavior, equilibrium asset prices, and expected returns was presented by Shu (2010). When the market is trending upwards and less risk is perceived, the investor behaves more optimistically. Whereas when the market is trending down, investor sentiment becomes relatively pessimistic, and investors will tend to wait and wait for the market until a revival begins. Although confidence in an asset can be recovered by evaluating the profitability of an investment. Therefore, investors should look at indicators that allow calculating expected returns in the short and medium run.

1.1 Research Motivation

Unexpected phenomena that cause such high-scale disruptions in the world, such as Covid-19, provide the opportunity for all those interested in the subject, to explore and to explain the event, making use of their own knowledge and applying different techniques or models. 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.

At this point, it can be assumed that the main motivation of this research is to understand, to analyze and to compare the behavior of the stock markets before and during the Covid-19 pandemic. Likewise, the purpose lies in the search for learning during the research process, applying knowledge already acquired and enriching the author herself with new badges.

1.2 Research objectives

This research has the primary objective of explaining and comparing the behavior of five stock indexes: Nasdaq 100, FTSE 100, CAC 40, DAX 30 and Nikkei225; during the following two periods. 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 focus on the daily return of each index and thirty of their listed stocks. The study inquiries into factors such as beta coefficient, total risk, systematic and unsystematic risk; that allows the application of Capital Asset Pricing Model and Jensen's alpha model.

To complement, this research also seeks to explain and compare the volatility of the stock markets during the periods considered above. Therefore, it seeks to calculate the daily volatility under the application of the Autoregressive models: ARCH and GARCH. The findings expect to answer the following research questions.

1. What are the return dynamics of the shares under study before and during the Covid-19 pandemic?
2. What are the risk dynamics of the stocks under study before and during the Covid-19 pandemic?
3. To what extent is the daily volatility of the stock markets affected by the conditional variance and by the adjusted conditional variance before and during the Covid-19 pandemic?

It is expected that the results obtained can explain the behavior of stock markets in five of the world's largest economies, the findings look forward to highlighting differentiations between the study periods and between countries. Thus, the research can serve as a basis for future research on the same topic that enables to make conclusions by country, sector, industry, or corporate level.

2 Literature Review

This section is divided into three subsections. The first part does a recapitulation of the behavior of financial markets in previous economic crises and the insights of other research in the matter. The second and third subsection explains the variables and models used in this research, in order to give a preview of the methodology of descriptive analysis of the behavior of stock markets before and during the financial crisis caused by Covid-19.

2.1 Historical perspective

It is known that history repeats itself, especially when certain coincidences that occur in different historical periods are perceived. In the financial market history, we find many examples of crisis that caused market crashes. Patel and Sarkar (1998, p. 265) defined a market crash as "an event when the regional price index declines, relative to the historical maximum, more than 20% for the developed markets, and more than 35% for the emerging markets".

Although the United States has initiated most of the economic crises that we have experienced in these last two centuries, the recent world crisis caused by Covid-19 has caused more critical impact in the stock markets around the world even in comparation with the financial crisis in 2008.

2.1.1 Oil crisis

As of 1950, many economies had recovered from the Great Depression and some of them were consolidated as areas of world wealth, an unbearable rivalry between Europe and the United States that appeared. While U.S.A consolidated as the greatest power, pressures were generated towards the dollar and its reserves were diminished by the long-lasting war in Vietnam. In the 70's, Egypt and Syria started a war against Israel (Yom Kippur War); because the main oil producers supported Israel, the countries that supported the other two rival countries, were forced to increase the price of oil, especially the United States. The dependence on the energy and the rise in the price of oil caused a sudden inflation and a general shortage of fuel, which broke the production chains and impacted the stock market. The New York Stock Exchange lost 97 billion dollars in six weeks as investors from oil producing countries began to invest in Latin American countries. (Marichal, 2010).

2.1.2 The Black Monday

On Monday, October 19, 1987, the Dow Jones stock index irrevocably sank like never before, falling by 508 points and losing 22,6% of its value. The S&P 500 index lost 57,86 points and registered a drop of 20,46%. While the NASDAQ fell 46 points and reported a drop of 11,35% in its value. Outside of the United States, the impact, was not as pronounced, but was evident. In fact, the other markets reacted after Wall Street had already bottomed out and investors were panicking. European stocks, the UK's FTSE 100 lost 10,8% on October 19, while the German DAX 30 index and the French CAC 40 index simultaneously fell 9,4%. Stock markets in the Asia-Pacific region were particularly affected; Nikkei 225 fell 2,4% on October 19 and then 14,9% on Tuesday, October 20; and Hang Seng Index fell 11,1 %on October 19, causing the Hong Kong stock market to close for four days to counter investor panic.

Some analysts believe that Black Monday was caused primarily by programmatic trading rather than purely economic factors. McKeon & Netter (2009) lists three determinants that caused the stock market crash in 1987. Firstly, the history of the efficient market says that the market reacted to some events such as the tensions of the USA and East, which led market participants to revalue stocks and lower prices by more than 20% in a single day. The second determinant was the trade deficit of USA, many sell orders caused a lack of liquidity. And the third determinant was the

behavior of investors who acted irrationally, as they pushed prices too high and during a significant drop, they panicked and sold senselessly, which significantly depressed prices.

2.1.3 The dotcom bubble

The dotcom bubble was a speculative bubble in the prices of shares in the internet sector, mainly in the USA markets, from the beginning of 1998 to February 2000. The high confidence of investors in this sector caused the internet sector to grow more of 1000% of its public capital and represent 6% of the market capitalization of the United States. While investors were hopeful, the dot.com bubble burst between 2000 and 2002, when the NASDAQ lost nearly 80% of its value and stock returns were fading.

The explanations of the causes of this bubble have been studied. Wollscheid (2012), explains that during this period, investors were under the "Feedback effect", when a stock they owned rose in price or when other investors made large amounts of money for owning a particular stock. In the long run, this generated a progressive price increase as more investors bought particular stocks and offered higher prices, the purchase prices were higher. In addition, Ofek & Richardson (2003) questioned the short selling restrictions to Internet stocks as a possible explanation for this bubble. Given the entry of irrationally optimistic investors into the market and the steep rise in prices of these attractive stocks, "pessimistic investors" considered these stocks to be "overpriced" and would like to sell short and get the markets back to trading levels at reasonable prices, but the size and volume of operations of optimistic investors were greater, so that this intention to stabilize prices and prevent the bursting of the bubble was vanished.

2.1.4 The Financial Crisis

The renowned Global financial crisis of 2008 was the first transcendental economic and financial phenomena of the 21st century, due to its rapid transmission This important event originated in August 2007 in the United States, in a scenario in which housing was overvalued and interest rates were very low. This caused families to go into debt and invest in homes. The banks took advantage of the opportunity and granted mortgages to those families, that were considered high credit risk. As mortgage loans were granted to these subprime families, the bank concentrated that loans in risky assets which were later traded in the financial markets. Because interest rates did not stay

low, many of the indebted defaulted on their homes. The tensions in the financial markets continued to grow so that the bursting of this bubble ended up drowning the banks and a lack of liquidity in the financial markets since those toxic assets were not backed by any guarantee of payment.

Given the importance of the US economy and its participation as a source and destination of portfolio investment, the effects on its stock market were transmitted almost immediately to other capital markets, affecting its operation in the short and long term. Due to the great impact, the literature of this event is extensive. Some authors have explained the behavior of the stock markets from different approaches. Grout & Zalewska (2016) proved in deep analysis of the collapse of the banking sector as a share of the stock market and the impact in the betas of the CAPM model of industrial and utility sectors in the G12 countries. In their work they underline the importance of the "Composition effect" a change in the market risk of a sector that is caused not by a direct change in that sector but by a change in another sector that affects the composition of the stock market. The authors found that even the crisis was not uniform even among the G12 countries, all countries with the pre-crisis market risk of the banking sector above one, experienced increase in market risk of industrials during the crisis, and all countries with pre-crisis market risk of the banking sector below one experienced decline in market risk of industrials. The scenario turned different for the utility sector, where the beta factor of the utilities sector did not experiment any composition effect, although the authors found that the beta of the utility sector falls in some countries and rises in others with increases in the beta outnumbering the declines.

Another research that demonstrated a cross-country analysis is the study carried out by Didier et al. (2011). In their major study, they discuss the factors that generate the correlation between stock market returns in the US and eighty-three other countries. It also highlights the importance of the different channels of crisis propagation, including real and financial linkages and the demonstration effect or wake-up scenario. The evidence demonstrates that those countries with high levels of portfolio inflows, more liquid and more developed stock markets were more correlated with the US market. The notable existence of an awakening in the first stage of the crisis was also demonstrated, in countries with the most vulnerable banking and corporate sectors there is a significant correlation between their stock markets and those of the USA. Despite the facts, the authors conclude that macroeconomic vulnerabilities do not seem to matter for

transmission in the context of the 2007-2008 crisis, they warn that this factor may be relevant in future crises.

2.2 Phenomenon of Risk-Return

This cross-sectional study in this text focuses on the analysis of five stock indexes which are made up of a set of listed securities. These securities, commonly known as stocks, are considered financial assets, since their value or benefit is an obligation of future money; that is, the possession of a unit of a stock or a share brings a benefit to the investor, by receiving dividends from the company that issues the share. The holding period return "HPR" is the return obtained from the investment of a share for a define period, it is calculated from the following formula where "D" represents the paid dividend, "P_n" represents the ending price of the stock and P_1 the beginning price of the retention period.

$$HPR\% = ((D+ P_n - P_1)/ P_1) * 100\%$$

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, which in turn generates a simple rate of return or known as **Realized rate of return**. These return measure the degree to which a gain or loss has occurred over the period the share was held. The calculation of this simple realized 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:

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

Nevertheless, for an investor it is extremely important to know what the future returns are before making an investment in any stock. To do this, it is possible to estimate the future **Expected rate of return** based on the "HPR"; often the expected return earned on a company's stock is a proxy for the cost of capital calculation.

Additionally, investors also consider the **Required rate of return**, the minimum return that the investor requires to accept the risk assumed by investment. "The required return could be

understood as the opportunity cost of an investment, the return that the investor could have obtained for a different project with a similar risk in the market" (Hundal et al., 2019, p. 6).

2.2.1 Financial Risk

Although everything that leads to a benefit also leads to a profit. In the financial field, we refer to risk as a "possible loss of money that means, directly, an impact on the financial system or one of the institutions that make it up" (Herrera Villalva & Terán Sunca, 2008, p. 142). Therefore, for investors it is crucial to know the level of **Total financial risk** that presents the investment, since the loss or profit that they will have depends on it. From a general perspective, the total financial risk represents the sum of systematic risk and unsystematic risk.

The **Unsystematic risk**, also known as "diversifiable risk", encompasses the set of factors specific to a company or industry, and which only affect the return on its stock. Gitman &Zutter, 2019 explains that unsystematic risk is the part of an asset's risk that is attributed to fortuitous causes and can be eliminated through diversification. This unsystematic risk arises from uncertainty or circumstance, that surrounds a company or by those of the sector to which it belongs, such as the degree of indebtedness, the quality of management, of its directors, fraud within the company or even a strike. Therefore, these events affect the price of the shares that have issued the company and the expectations of buying and selling by investors.

On the other hand, there is the **Systematic risk** or market risk, which refers to the possibility of losses in a market because of risk factors, e.g., inflation, incidental international devaluations, general state of the economy, and other events. (Gitman & Zutter, 2019). Additionally, systematic risk cannot be eliminated through diversification, so it affects the set of assets found in a market and in any investment portfolio, making the level of this risk extremely important and essential for investors.

2.2.2 Beta coefficient

To carry out an approach to the calculation of risk and thus determine what is the maximum loss that can be suffered, it is necessary to use the variables obtained from the observations over time of the market factors. Researchers attempted to use the Beta coefficient "β" as a measure of

systematic risk. Gitman & Zutter, 2012 define beta coefficient as the degree of movement of the performance of an asset in response to a change in the market performance, this coefficient represents the slope of a characteristic line, which relates the individual performance of an asset with the performance of the market portfolio, that is, it expresses the sensitivity, variability, or degree of movement of the returns of an asset in response to the change in market returns. If the beta coefficient of the stock is greater than one, it represents a systematic risk greater than that of the market and is considered a risky investment, while a beta coefficient less than one, it has a systematic risk lower than that of the market and represents a defensive investment.

2.2.3 Capital asset pricing model

Up to this point, some variables to consider when you want to make an investment have been explained. Different models exist in the literature that relates the return and risk of financial assets. In the early 1960s William Sharpe developed the **Capital asset pricing model (CAPM).** The CAPM is known as the formula for calculating the expected return of any risky asset class compared to systematic market risk. The formula is as follows:

$$ER_i = R_f + \beta_i \, (ER_m - R_f)$$

Where "ER_i" represents the expected return of the risky asset, "R_f" is the risk-free rate, β is the beta coefficient, and "ER_m" is the expected market return. In a risk-free market, the expected return would be equal to the risk-free rate, nevertheless, in the real market, investors expect to assume additional risk, thus the second part of the above formula "$\beta i \, (ER_m - R_f)$" explains that the return on the risk premium is above the risk-free rate and simultaneously the risk premium is adjusted by the beta coefficient "β" (Droussiotis, 2020).

The CAPM is a model that has been applied over the years and several researchers have used to make some conclusion or test the model's validity, especially in times of economic crisis. Vieito et al. (2015) tested whether the Financial crisis of 2008 had any positive impact on the G7 indexes (Canada, France, Germany, Italy, Japan, UK and US). The authors base their analysis on CAPM statistics and complement it with an analysis of mean variance, Hurst exponent, runs test, multiple variance ratio test, and stochastic dominance tests. According to the CAPM results, they conclude that all stock indexes The G7 markets perform better after the financial crisis, while the results of

the run test and the multiple variance ratio tests show that although the G7 markets were still not as efficient before the crisis, and their efficiency has improved after of the financial instability of 2008.

Recently, Airinen (2021), conducted a study to verify the effectiveness of CAPM during the Covid-19 pandemic. To do this, the author analyzed the beta returns of one hundred stocks listed on the S&P 100, DAX, FTSE 100, OMX Helsinki 25 and Nikkei 225; and found that there is a significant difference between the returns of stocks with high and low betas during the Covid-19 pandemic. Thus, he concluded that the CAPM is invalid on the five selected indexes during unfavorable market conditions.

2.2.4 Jensen's Alpha

Moreover, in the late 1960s Michael Jensen developed a formula that determines the average performance above or below the expectation calculated by the CAPM. This indicator, known as Jensen's Alpha, compares the difference obtained by an asset against a benchmark with the same amount of risk. The formula is as follows:

$$\alpha = R_i - (R_f + \beta_i (ER_m - R_f)) = R_i - CAPM$$

Where α represents the Jensen's alpha coefficient, "R_i" is the realized return on the investment of the portfolio. If Jensen's alpha is positive, it represents the excess return over the CAPM, while a negative alpha says that the return is not even achieving the expected return for the systematic risk assumed. This indicator allows us to contrast different investment portfolios, any type of asset or even assets in different periods of time, as long as a stock market indicator is used as a reference in which we can make a comparison. (Droussiotis, 2020)

2.3 New measures of volatility- ARCH and GARCH models

Given the existence of instability in the financial stock markets over the years, a great fear of financial risks has exponentially grown by investors. As it is known, one of these risks is the potential loss that an investor may suffer due to variations in the prices that are registered in the stock markets. Easy access to information allows the application of estimation and/or prediction

methods of the volatility of any underlying asset at risk. **Volatility** is a statistical indicator expressed as a percentage and is calculated by the standard deviation or by the squared root of the homoscedastic variance recorded by an underlying financial series asset with respect to the average of its historical price in a given period. The formula to calculate the daily volatility is as follows:

$$\sigma=\sqrt{((\sum(r_i-m)^2)/(n-1))}$$

Where "σ" is the standard deviation, "r_i" represents the return at time "i", "m" is the mean of all data points and "n" is the number of data points.

Given the importance of the volatility variable, it led academics in the past century to create statistical models to model the volatility of time series. Box and Jenkins (1974) developed ARIMA (Autoregressive Integrated Moving Average) statistical models for time series that take into account the dependence between the data and each observation at an exact time point is modeled in terms of previous values. These models are based on an autocorrelation structure and are relatively easy to implement and viable for the analysis and forecast of certain time series.

Nevertheless, the mentioned time series models may not be appropriate for modeling financial time series, because they assume a homoscedastic variance within the time series and financial time series do not have a constant volatility; actually, the financial time series present a heteroskedastic variance, since the errors are not the same in all the observations made. Furthermore, in the financial time series there are long periods of high volatility followed by periods of low volatility, which provokes the presence of agglomeration.

Consequently, the academics made possible to explain that non-constant variance can be correlated over time. Engle (1982) introduced a new class of stochastic processes called **ARCH** (Autoregressive conditional heteroskedasticit) model, in which the **Conditional variance** of past information is not constant and depends on the square of past information, thus this model allows to explain the agglomeration or clustering of volatility that occurs in series of financial assets, which are characterized by being non-linear series. Usually, the conditional variance can be expressed as "σ^2_t"

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

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 "$\sigma^2 t$", to depend on the prior value of the squared error:

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

where the parameter "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.

Subsequently, Bollerslev (1986) generalized the ARCH model by proposing **GARCH** (Generalized autoregressive conditional heteroskedasticit) model in which the conditional variance depends not only on the squares of the disturbances, as in ARCH, but also on the conditional variances of previous periods. In GARCH model, the "σ^2_t" becomes recursive and adjusted, 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. This 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 this equation, "σ^2_t" is interpret as the **Adjusted conditional variance**, the parameter "ω" represents the variance of an initial time period as a constant term. The coefficient "α^1" 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.

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 five 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 indexes, also examines the stock market volatility for the seven indexes using the regression models. The studied found that ARCH effects are highly significant for all G7 indexes, indicating the presence of volatility conglomeration in the data series. The results of the GARCH and GJR-GARCH models reveal that the named COVID-19 variable has a significant positive impact on the conditional variance of the G7 indexes, implying that the coronavirus has increased stock market volatility in these countries.

3 Research Framework

In this study, the methodology is considered as a theoretical and systematic analysis of applied methods, encompassing concepts such as research objective, research approach, time horizon, limitations, and quantitative or qualitative techniques. "The methodology helps to understand not only the products of scientific research, but the process itself" (Patel &Patel, 2019).

According to the methodology followed in this research, this text has firstly a descriptive objective since it intends to systematically describe the behavior of the financial markets from a descriptive analysis of quantitative variables. Consequently, there is an explanatory objective that looks forward to clarifying "why and how" there is a relationship between the variables under study: annual realized rate of return, financial risk, systematic risk, unsystematic risk, beta coefficient,

annual expected rate of return, realized volatility, conditional volatility, and conditional adjusted volatility. This implies that the research has a quantitative approach given that the collection of data, analysis of data and description of the results use quantitative techniques.

The time horizon of data analyzing is made up of two study periods. The first period called the *Pre-Covid-19 period* covers 5 years of study from January 2, 2015, to December 30, 2019. The second period named as the *Covid-19 period* covers two years of study from January 2, 2020, to December 30, 2021. Because it is practically not possible to analyze all the stocks markets across the world, on that account, this research is limited to analyze five of the most significant indexes in the world and thirty stocks of the companies listed in each index. The general findings of each index are detailed explained, and although individual results have been obtained for each selected stock of each index, only particular findings are mentioned in the corresponding sections of the text.

3.1 Data

The daily closing price of Nasdaq 100, FTSE 100, CAC 40, DAX 30, and Nikkei 225 Indexes, during the *Pre-Covid-19 period* and *Covid-19 period* were collected. As well, the daily closing price of the thirty selected stocks of each index over the same time horizons were computed. It is worth to mention that the thirty stocks of each index were selected for the analysis purpose in such a manner that they represent large, medium and small companies based on their market capitalization, i.e., ten stocks with large capitalization, ten stocks with mid capitalization and ten stocks with small capitalization were selected within the market capitalization range of each index. The stocks selected belong to different sectors (Appendix 1) with the aim of maintaining diversification and avoiding similar results in companies of the same business line. Noteworthy, each closing price was obtained from each asset was extracted from the same financial website.

3.2 Data Analysis

The Data Analysis was divided into two phases. Over the first phase we obtained: the daily and annual realized rate of return; the total, systematic and unsystematic risk; the beta coefficient; the annual expected rate of return; and the Jensen's Alpha coefficient of each index and each selected stock during both periods under study.

We can assume that up to the first section, a superficial analysis of the behavior of the indexes and their stocks based merely on returns has been made. As the name of this research makes clear, it seeks to show a new approach to the study of the return-risk and volatility of indexes and stocks. Thus, the second phases consist in the calculation of the volatility of each index and each selected stock based the on the realized variance, conditional variance from ARCH model and adjusted conditional variance from GARCH model.

In such a way, the results obtained in the first section of CAPM and Jensen Alpha, stand out for their simplicity of implementation and for their ability to explain and compare during *the Pre-Covid-19 period* and the *Covid-19 period*. On the other hand, the ARCH and GARCH models enhance this research by providing daily accurate explanations of the heterogeneous behavior of the indexes and their stocks during the study period, as these models consider the past information of the variable. Additionally, these models recognize its volatility as a highly explanatory factors of their past and present behavior and even a logical prediction of their future behavior.

Noteworthy, all data was storage and computed on Microsoft Excel worksheets. Depending on the variables to be calculated, multiple formulas and/or tools of the program in use were applied.

3.3 Description of variables

Return

Given that the basis of the investigation is the daily return or also refer as a "realized return". Each return was obtained based on the daily closing price of each asset. Where, "P_{m1}" represent the closing (ending) index price, and "P_{m0}" is the initial index price; "P_{i1}" means the closing (ending) stock price and "P_{i0}" represents the Initial stock price.

$$\textbf{Daily index return} = (P_{m1}-P_{m0})/P_{m0}$$

$$\textbf{Daily stock return} = (P_{i1}-P_{i0})/P_{i0}$$

Subsequently, it was calculated the average daily return of each index and each selected stock in the two periods, and then it was obtained their annual realized return from both periods, which is expressed in the following formula and where "252" represents the average number of trading days per year on the stock exchanges.

$$\textbf{Annual index return } (\mathbf{R_m}) = ((\text{Average daily index return} + 1)^{252} - 1) * 100$$

$$\textbf{Annual stock return } (\mathbf{R_i}) = ((\text{Average daily stock return} + 1)^{252} - 1) * 100$$

Beta

Commonly the beta coefficient is calculated manually through the following formula; where "σ_m^2" represents the variance of market annual returns and "Cov" means the covariance of annual index return "R_m" and annual stock return "R_i".

$$\boldsymbol{\beta}\ \mathbf{(i)} = \text{Cov}((Ri, Rm)/\ \sigma_m^2$$

To take advantage of the facilities provided by the Microsoft Excel program, the "SLOPE" function was used to measure beta of each selected stock, using daily index returns and daily stock return as the parameters of the function.

Risk

Starting from the fact that the total risk of any asset is made up of the systematic risk and the unsystematic risk, the total annual risk of each selected stock was calculated, using the predetermined "Standard deviation" function provided by the Microsoft Excel program, and subsequently the output was multiplied by the square root of 252. The deduction of the annual systematic risk of each stock required the intervention of its respective beta coefficient "β_i" and annual total risk of the index "σ_m" in which it is listed.

$$\textbf{Annual stock systematic risk} = \beta_i * (\sigma_m)^{252}$$

And therefore, it was possible to compute the annual unsystematic risk through a simple clearance of the total annual risk formula.

Annual stock unsystematic risk = Annual stock total risk– Annual stock systematic risk

CAPM

Having already computed the variables required in the Capital asset pricing model formula, the expected annual rate of return "Er_i" for each stock in each period was obtained. The value of the risk-free rate "R_f" is equal to the average value of the "10-Year Bond Rate "of the country of origin of each market index of the corresponding year of study, i.e., the risk-free rate used for selected stocks listed on the FTSE 100 in the Covid-19 period, corresponds to the average value of UK 10-Year Bond Rate from 2020-2021.

$$\mathbf{ER_i} = R_f + \beta\,(i) * (R_m - R_f)$$

Jensen's Alpha

To finalize this first phase, the Jensen's alpha coefficient of each selected stock during the two periods was easily calculated by the following formula:

$$\textbf{Jensen's Alpha} = R_i - ER_i$$

Volatility-

The second phase of data analysis corresponds to the analysis of the daily volatility of each index and each selected stock, based on the calculation of the realized volatility, conditioned volatility of the ARCH model and adjusted volatility of 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 and its formula is as follows.

$$\textbf{Realized volatility } (\boldsymbol{\sigma^2}) = 100 * \sqrt{((252/n) * \sum R_t^2}$$

Where "$\sigma^{2"}$ is the realized volatility; "t" is a counter representing each trading day; "n" is the number of trading days in the measurement period, as we know, "252" is a constant representing the approximate number of trading days in a year and "R_t " is the continuously compounded daily returns. "R_t"can be calculated by the formula:

$$\mathbf{R_t}=\text{Ln} *(P_t/P_{t-1})$$

Where "Ln" represents the natural logarithm; "P_t" is the closing asset price at day "t" and "P_{t-1}" is the asset reference price at day immediately preceding day "t". To make the most of Microsoft Excel tools, in this research was possible to calculate the daily realized volatility through the "Solver" tool.

Likewise, the daily conditional volatility of the ARCH model and the adjusted conditional volatility of the GARCH model were obtained, thus each parameter of the respective model was computed using the same tool "Solver". The constant term "ω", the coefficient "α_1" and the prior value of the squared error "u^2_{t-1}"were found for the ARCH model:

$$\textbf{Daily conditional volatility } (\sigma^2_t) = \omega + \alpha_1 u^2_{t-1}$$

And the constant term "ω", the coefficient "α_1", the prior value of the squared error "u^2_{t-1}", the coefficient "β_1" and the historical squared lagged variance in a period "σ^2_{p-1}" were computed for the GARCH model.

$$\textbf{Daily adjusted conditional volatility } (\sigma^2_t) = \omega + \alpha_1 u^2_{t-1} + \beta_1 \sigma^2_{p-1}$$

4 Results

In parallel to the structure of the previous section, this section is made up of two parts that contains descriptive analysis and graphical analysis made on Microsoft Excel program and Statistical Package for the Social Sciences (SPSS) software. The tables and graphs shown in this section contain summarized information, particular findings of each index and each selected stock are only mentioned. Whole results of each index and stock can be found on Appendix section.

4.1 Risk-Return

The first section contains a descriptive analysis of the annual return across indexes of each period, a Paired sample T-test of beta in both periods, a graphical analysis of CAPM and a descriptive analysis of the Jensen's Alpha.

4.1.1 Return

Table 1 shows the descriptive analysis of the annual returns of the thirty selected stocks during the *Pre-Covid-19 period*. The Nikkei 225 index had the highest nullified mean return of 0,614, although it also had the highest variance of 2,871 and there was a large difference between the maximum and minimum annual return. Followed but with a significantly lower mean of annual return of 0,295, the DAX 30 had the symmetry value of 5,358, which suggests that the annual return of the German index was highly skewed but its extreme positive kurtosis of 29,092 indicates a distribution where most all returns lie in the tails of the distribution rather than around the mean. Nasdaq 100 showed a mean of the annual return of less than 0,201, but its skewness of 0,018 indicated that the computed returns were fairy symmetrical and the negative kurtosis value of -0,305 indicated a more peaked than normal distribution. The CAC 40 index stood out for the symmetry of the data and for its extreme positive kurtosis. FTSE 100 showed the lowest mean of the annual return, it had a moderate fairy symmetry of 0.101 and a kurtosis close to zero indicating a near normal shape.

Table 1 Descriptive Analysis Annual Return 2015-2019

Stock Index	Nasdaq 100	FTSE 100	CAC 40	DAX 30	Nikkei 225
Mean	0,201	0,086	0,151	0,295	0,615
Std. Error of Mean	0,026	0,020	0,032	0,184	0,309
Median	0,222	0,069	0,119	0,079	0,094
Mode	0,255	-0,169	-0,069	-0,050	-0,166
Std. Deviation	0,141	0,109	0,173	1,007	1,694
Variance	0,020	0,012	0,030	1,014	2,871
Skewness	0,018	0,101	2,197	5,358	2,852
Kurtosis	-0,305	0,541	7,434	29,092	6,826
Range	0,547	0,495	0,902	5,639	6,277
Minimum	-0,056	-0,169	-0,069	-0,050	-0,166
Maximum	0,491	0,326	0,833	5,589	6,111

Sum	6,044	2,567	4,530	8,863	18,436
Count	30	30	30	30	30

Peculiar changes in the annual returns in the *Covid-19 period* are recorded in Appendix 3. The mean of the Nasdaq 1000 and CAC 40 increased by 2677 and 427 basis points respectively, while the mean of the other indexes decreased by 266 basis points for the FTSE. 100, 780 base points for DAX 30 and 5872 base points for Nikkei 225. The variance of the Nasdaq 100, FTSE 100 and CAC40 increased, especially that of the Nasdaq 100 index which reaches 43%, while the variance of the DAX 30 and Nikkei 225 decreased. The asymmetry has also changed, the annual returns of the Nasdaq 100, DAX 30 and Nikkei are highly skewed, and the FTSE 100 and CAC 40 are symmetrical. Finally, there is excess kurtosis for Nasdaq 100, DAX 30, and Nikkei 225; and the negative kurtosis of FTSE 100 and CAC 40 makes it clear that they had fewer tails than that of a normal distribution

Table 2 Descriptive Analysis Annual Return 2020-2021

Stock Index	**Nasdaq 100**	**FTSE 100**	**CAC 40**	**DAX 30**	**Nikkei 225**
Mean	0,469	0,059	0,194	0,217	0,027
Std. Error of Mean	0,120	0,029	0,037	0,053	0,032
Median	0,341	0,064	0,206	0,137	0,006
Mode	0,007	-0,318	-0,041	-0,145	-0,232
Std. Deviation	0,656	0,157	0,205	0,292	0,174
Variance	0,430	0,025	0,042	0,085	0,030
Skewness	4,207	-0,015	0,254	1,793	1,027
Kurtosis	20,463	-0,008	-1,049	4,244	1,798
Range	3,653	0,710	0,694	1,364	0,802
Minimum	0,007	-0,318	-0,123	-0,145	-0,232
Maximum	3,659	0,391	0,571	1,219	0,570
Sum	14,074	1,768	5,810	6,524	0,819
Count	30	30	30	30	30

Analyzing the annual returns of the thirty stocks of each index (Appendix 2 and Appendix 3) it was found that twenty-one stocks of the Nasdaq 100 index increased the annual return during the Covid-19 period, particularly the stocks belonging to the Information Technology and Communication Services sector (e.g. Apple Inc, Alphabet, Meta, Baidu, DocuSign); stocks from the

Consumer Discretionary sector presented little changes while stocks from the Travel and Accommodation and Healthcare sector (e.g., Marriott International and Seagen) reduced their annual return during the second study period. The British index showed more mixed and declining results since almost 50% of the stocks of different sectors reduced their annual return during the pandemic, remarkably stocks from the Energy sector registered negative annual returns (e.g. Shell and BP). The changes of the CAC 40 index are more balanced, only ten stocks from different sectors registered decreases in their annual return from 2020-2021, the rest of the stocks increased their return or stayed same to the previous period. DAX 30 also stood out for various changes that do not depend precisely on the sector, because stocks from the same sector such as Mercedes Benz, increased its annual return, and BMW, registered a negative annual return. The annual return of more than half of the selected stocks of the Nikkei 225 diminished, although stocks from the Information Technology and Consumer Discretionary sectors remained on the sidelines compared to the *Pre-Covid-19 period*.

4.1.2 Beta

To analyze the betas of the selected assets of each index between the two periods in question, the paired samples T-test was executed in the "SPSS" software. Table 3 shows the results of the test.

Table 3 Beta Paired Samples Test

	Mean	Std. Deviation	Std. Error Mean	t	Sig. Two-Sided p
β Nasdaq 100 "Covid-19" - "Pre Covid"	0,022	0,298	0,054	0,404	0,68
β FTSE 100"Covid-19" - "Pre Covid"	0,064	0,411	0,075	0,853	0,40
β CAC 40 "Covid-19" - "Pre Covid"	0,074	0,287	0,052	1,40B	0,17
β DAX 30 "Covid-19" - "Pre Covid"	0,049	0,440	0,080	0,609	0,54
β NIKKEI 225 "Covid-19" - "Pre Covid"	0,080	0,383	0,070	1,146	0,26

According to the results obtained in the paired samples t-test, it is seen that the mean beta difference between the *Pre Covid-19 period,* and the *Covid-19 period* is greater in the Nikkei 225 index, since it increases by 0,08, however the p-value greater than 0,05 of all the indexes indicates that the change in the mean of the betas between the two periods is not significant. These

outputs rule out the assumption that the change in beta has changed considerably during the Coronavirus pandemic.

4.1.3 Risk

Table 4 shows the average of the total risk, the unsystematic risk, the systematic risk and the beta of the thirty selected stocks of each index in the *Pre-Covid-19 period*. The Nikkei had the highest mean in all types of financial risks. Except for the CAC 40, the mean of systematic risk of all indexes was lower than the unsystematic risk and we can say that the highest average beta belonged to the FTSE 100.

Table 4 *Risk Pre Covid-19 period* 2015-2019

Stock Index	Total Risk	Unsystematic Risk	Systematic Risk	Beta
Nasdaq 100	0,309	0,165	0,144	0,842
FTSE 100	0,260	0,131	0,128	0,933
CAC 40	0,260	0,119	0,153	0,911
DAX 30	0,408	0,254	0,154	0,880
Nikkei 225	0,702	0,538	0,164	0,844

During the Coronavirus pandemic, (Table 5) an increase in the mean of beta of all the indexes was noted, thus the mean of the systematic risk also increased. Nasdaq100 showed the highest increase in the average systematic risk of 1054 basis points, where stocks such as Apple, Tesla or KLAC increased their systematic risk by more than 100% (Appendix 2); followed by CAC 40, the stocks with the greatest changes in their systematic risk belong to the industrial sector, e.g., Airbus, Vinci and Bouygues. Meanwhile, the stocks from the Automotive sector of DAX 30, appeared to have a higher Systematic risk during the *Covid-19 period*; and within the FTSE 100, it is noted that the stocks of Healthcare sector were more stable and did not increase their systematic risk as critically as the stocks from the Energy and Travel and accommodation sector. The Nikkei 225 index only increased the average systematic risk by 443 basis points, but it showed a

significant reduction in unsystematic risk of 3,724 basis points, since stocks such as Daiwa Securities, Meiji Holdings or Haseko decreased their systematic risk during the pandemic.

Table 5 *Risk Covid-19 period* 2020-2021

Stock Index	Total Risk	Unsystematic Risk	Systematic Risk	Beta
Nasdaq 100	0,413	0,163	0,250	0,864
FTSE 100	0,387	0,162	0,225	0,998
CAC 40	0,349	0,102	0,247	0,986
DAX 30	0,367	0,132	0,236	0,929
Nikkei 225	0,374	0,166	0,209	0,925

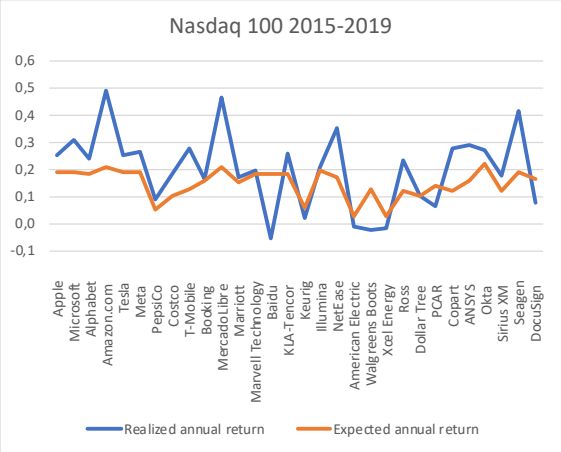
4.1.4 Cappital Asset Pricing Model

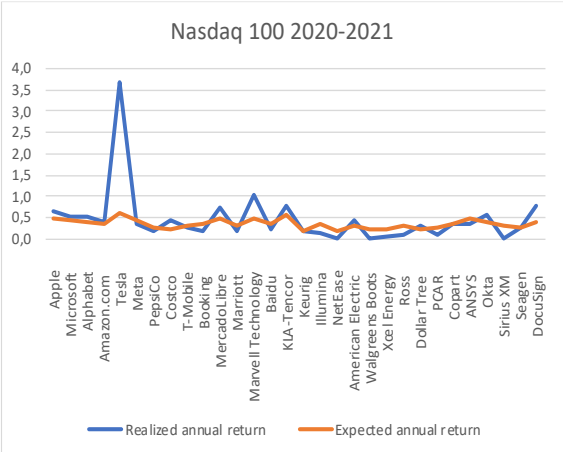
According to CAPM, there were variations between the expected return and the actual performance of the selected assets from each index in the two study periods. Figure 1 shows the comparison between the expected annual rate of return and the realized annual rate of return in both periods. Before the Pandemic, the realized annual return of most of the selected Nasdaq 100 stocks exceeded the expected annual return, from which some stocks from the Consumer Discretionary sector industries (i.e. Amazon and Mercado Libre) had a better real performance than expected, during the pandemic, this leadership passed into the hands of Tesla which performed six times better than expected; It should be noted that none of the selected stocks recorded negative returns, but stocks from the Travel and Accommodation and Communication services sector underperformed than expected.

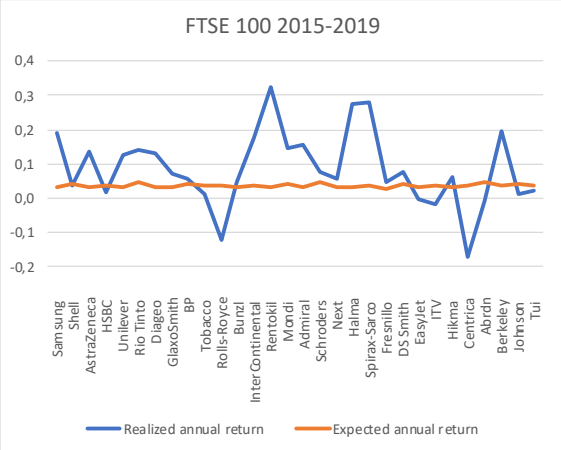
Although the expected annual return was considerably homogeneous across FTSE 100 stocks in each period, the realized annual returns are higher in the *Pre-Covid-19 period*. Before the pandemic, there were already stocks that underperformed, such as Rolls Royce or HSBC, but during the *Covid-19 period*, there was an increase in the number of stocks that underperformed than expected. Indeed, the variations between the expected and the realized return were more evident between the CAC 40 and DAX 30 stocks, since during the pandemic, almost half of the thirty selected stocks underperformed than expected. Finally, before the pandemic, Nikkei 225

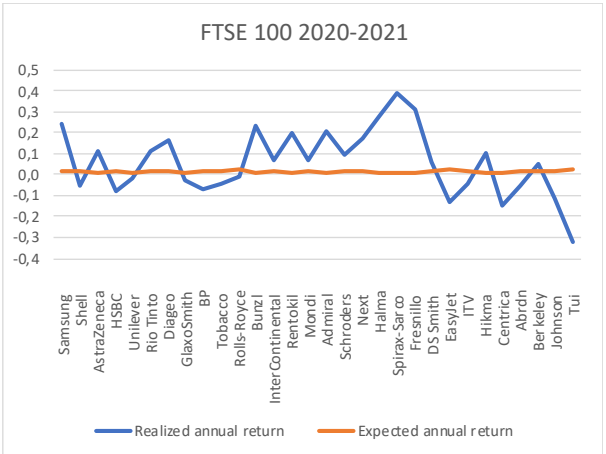
stocks performed really similar to the expectances, except for some stocks with surprisingly better performance than expected annual returns such as NEC and Mitsubishi, nevertheless during the *Covid-19 period* only 4 of the selected stocks (NEC, Minebea, CyberAgent and Chiyoda) managed to overperform than expected.

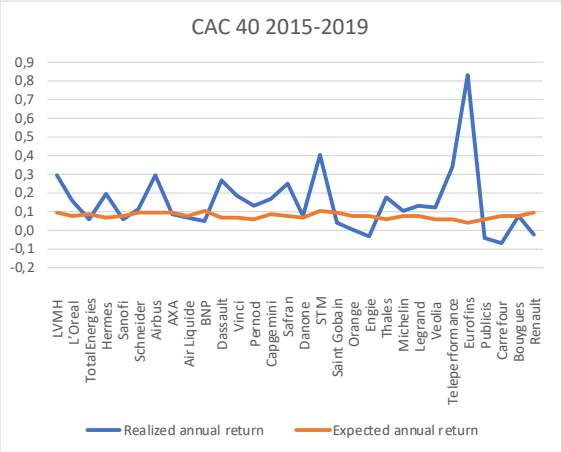
Figure 1 Annual realized return and Annual expected return during *Pre-Covid-19 period* and *Covid-19 period.*

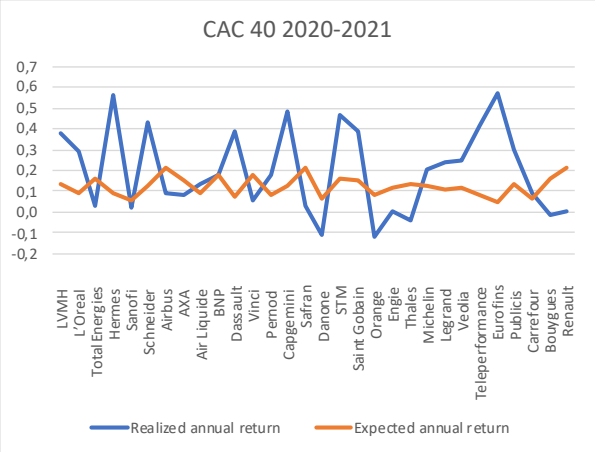


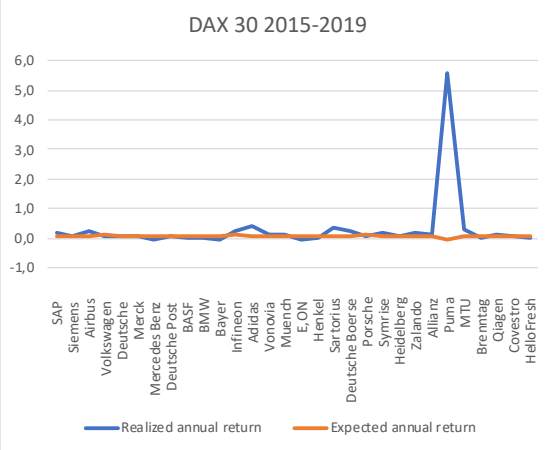


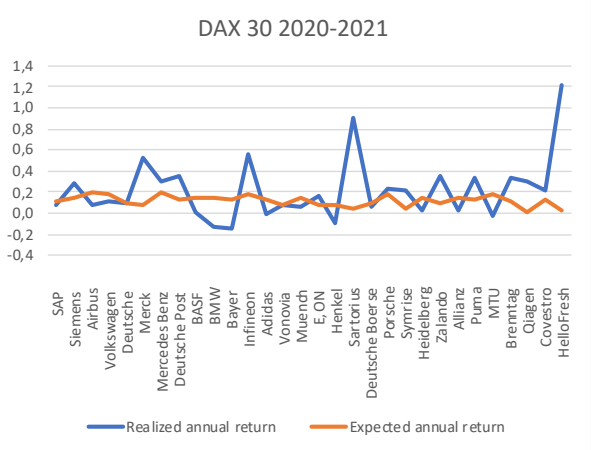


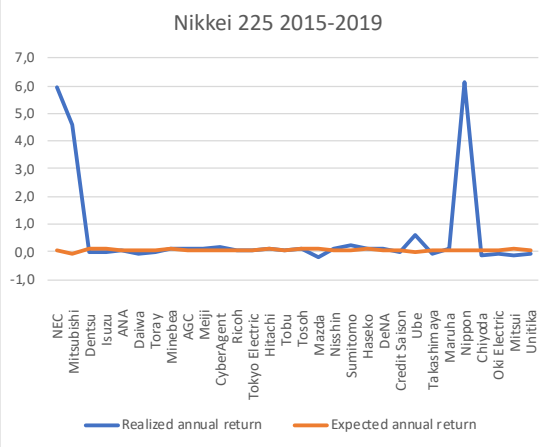


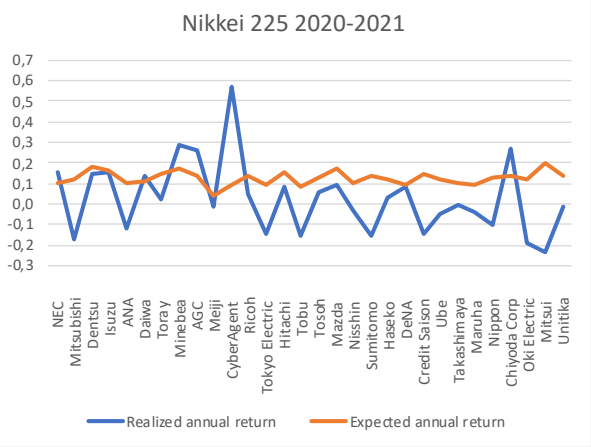












4.1.5 Jensen's Alpha

Tables 6 and 7 summarize the average of Jensen's Alpha of each index during the two periods. In the run up to the pandemic, average alpha was positive across all indexes; Nikkei 225 had the highest alpha, followed by DAX 30, CAC 40, FTSE 100 and Nasdaq 100 in succession. Nasdaq 100 was the only one with a high negative skewness and CAC 40, DAX 30 and Nikkei 225 stand out for

their excess kurtosis. During the pandemic, Nasdaq 100 average alpha took the lead, followed by DAX 30, FTSE 100 and CAC 40 average alphas which did not change greatly, compared to Nikkei 225 that had a negative average alpha. FTSE 100 and CAC 40 are roughly symmetric, while the other indexes are highly skewed. Finally, FTSE presented a negative kurtosis, which indicated that its distribution was very flat, while Nasdaq 100, DAX 30 and Nikkei 225 presented an excess of kurtosis, that is, their distributions were too peaked.

Table 6 Descriptive Statistics Jensen's Alpha 2015-2019

Stock Index	Nasdaq 100	FTSE 100	CAC 40	DAX 30	Nikkei 225
Mean	0,052	0,049	0,074	0,226	0,543
Std. Error of Mean	0,021	0,020	0,033	0,188	0,312
Median	0,055	0,030	0,042	0,012	0,016
Mode	-0,240	-0,205	-0,142	-0,139	-0,270
Std. Deviation	0,113	0,110	0,179	1,030	1,710
Variance	0,013	0,012	0,032	1,061	2,923
Skewness	-0,226	0,129	2,349	5,353	2,832
Kurtosis	0,711	0,520	8,455	29,057	6,684
Range	0,521	0,500	0,939	5,779	6,322
Minimum	-0,240	-0,205	-0,142	-0,139	-0,270
Maximum	0,281	0,295	0,797	5,640	6,052
Sum	1,567	1,458	2,223	6,783	16,276
Count	30	30	30	30	30

Table 7 Descriptive Analysis Jensen's Alpha 2020-2021

Stock Index	Nasdaq 100	FTSE 100	CAC 40	DAX 30	Nikkei 225
Mean	0,107	0,044	0,075	0,097	-0,098
Std. Error of Mean	0,107	0,029	0,040	0,058	0,032
Median	-0,025	0,048	0,062	0,026	-0,099
Mode	-0,298	-0,076	-0,209	-0,285	-0,434
Std. Deviation	0,587	0,159	0,217	0,317	0,176
Variance	0,345	0,025	0,047	0,101	0,031
Skewness	4,573	-0,015	0,350	1,863	1,042
Kurtosis	23,147	0,001	-1,021	4,505	2,875
Range	3,339	0,720	0,734	1,478	0,914

Minimum	-0,298	-0,340	-0,209	-0,285	-0,434
Maximum	3,041	0,379	0,525	1,194	0,480
Sum	3,198	1,311	2,252	2,907	-2,938
Count	30	30	30	30	30

4.2 ARCH and GARCH models

This second part contains the graphical analysis of the volatility analysis under the GARCH and ARCH models. This section is divided into two parts, first the results of the volatility analysis of the *Pre-Covid-19 period* is reflected and then the analysis of the *Covid-19 period* is made, as well the results of the *Covid-19 period* is compared with the results of the previous period.

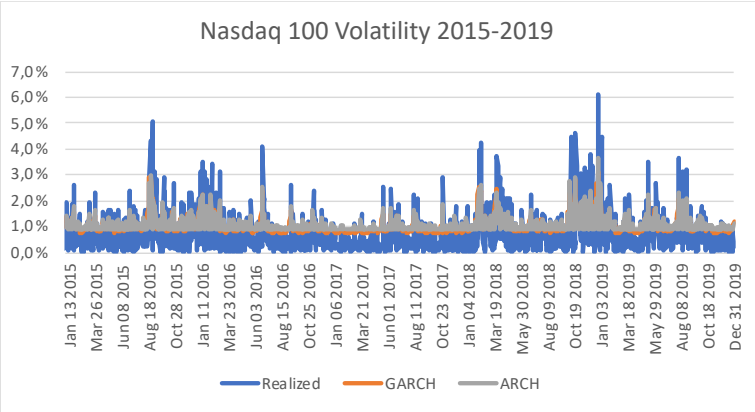
Each part contains graphs that compare the realized volatility, the conditional volatility from the ARCH model and the adjusted conditional volatility from the GARCH model based on the daily returns of each stock index as a whole; findings from the thirty selected stocks are only mentioned (Appendix 4 and Appendix 5 show the whole results of each index and selected stock from each model during both study periods).

4.2.1 Volatility during *Pre-Covid-19 period*

Starting with the analysis of the Nasdaq 100 index (Figure 2), according to the ARCH model, the volatility of the Nasdaq 100 from January 2015 to December 2019 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 realized volatility and from 0,9% to 3% of adjusted and conditional 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. According to the coefficients obtained, the volatility of the assets of the Information Technology sector depends to

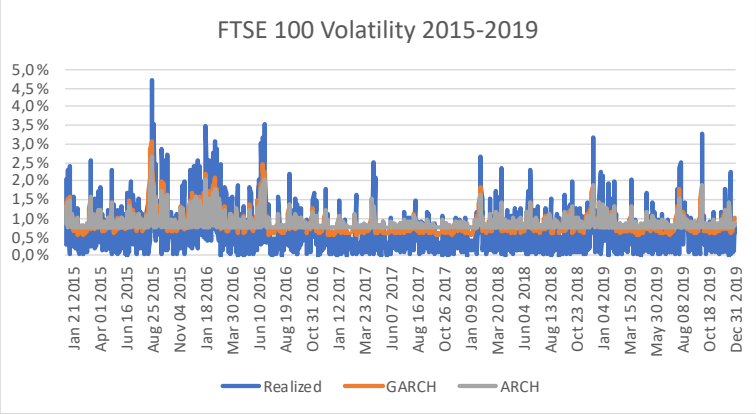
a greater extent on the variance of a previous day and the adjusted variability of the *Pre-Covid-19 period* in both models, although there are exceptions such as the Okta stock, where the coefficients of both models are equal to 0.

Figure 2 Nasdaq 100 Volatility 2015-2019



Similarly, the daily variances of the FTSE 100 index (Figure 3), 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 FTSE 100 index. The results of the thirty selected stocks are more varied than in the Nasdaq 100, since stocks from the same sector differ in volatility in the same periods in ARCH and GARCH models.

Figure 3 FTSE 100 Volatility 2015-2019



On the other hand, the Europeans CAC 40 (Table 4) and DAX 30 (Figure 5) indexes 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 indexes, these indexes present fewer high peaks. As well, the volatility of the selected assets of the CAC 40 industrial sector, show higher alpha coefficients in ARCH and beta coefficients in GARGH than the other stocks.

Regarding the Nikkei 225 index (Figure 6), periods of high volatility are reflected in conglomerations starting in September 2015. Likewise, the European indexes, 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 4 CAC 40 Volatility 2015-2019

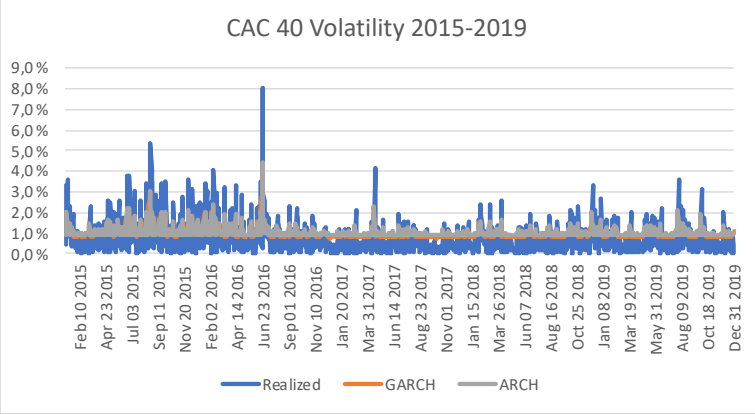


Figure 5 DAX 30 Volatility 2015-2019

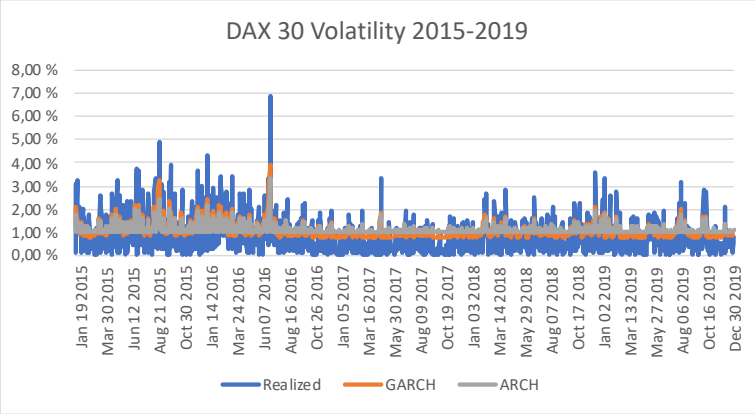
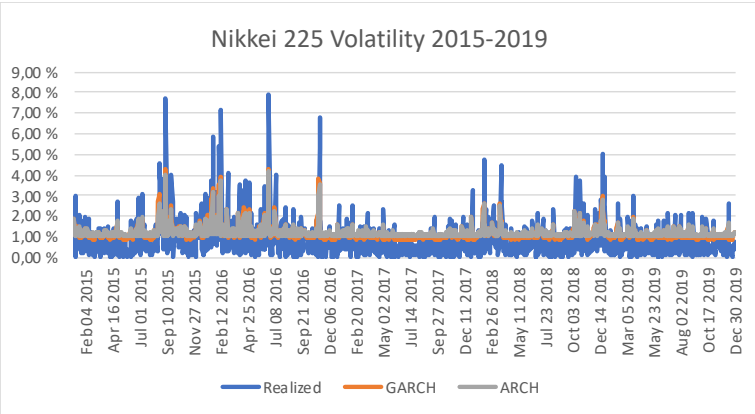


Figure 6 Nikkei 225 Volatility 2015-2019



4.2.2 Volatility during *Covid-19 period*

In this section, some of the findings of the reactions of the indexes 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 7) 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 indexes in both periods. That same day, the conditional volatility in the ARCH model and the adjusted conditional volatility of the GARCH model remain at 4,21% and 4,30% respectively, however, days before the great fall, 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. In addition to this, of the thirty selected stocks from the Nasdaq 100 index, 70% of them increased the ratio of their volatility in relation to the conditional variance of a previous day and to the conditional variance adjusted during the Pandemic; those stocks with coefficients 0 in Alpha and Beta in the previous period, show divisible values in this period.

The FTSE 100 index (Figure 8) registers its highest point of volatility one day before that of the Nasdaq 100 index, with a realized volatility reaching 10,86%, and conditional volatility 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 Nasdaq 100 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 coefficients greater than the previous period, since volatility is explained at 41,04% by the conditional variance and 48,3% by the adjusted conditional variance. The increase in the GARCH coefficients is also seen in the thirty stocks, since stocks such as Samsung or Hikma, which had registered a low dependence of volatility on the adjusted conditional variance of the period prior to the pandemic, have increased their dependence to more than 50% from 2020-2021.

Figure 7 Nasdaq 100 Volatility 2020-2021

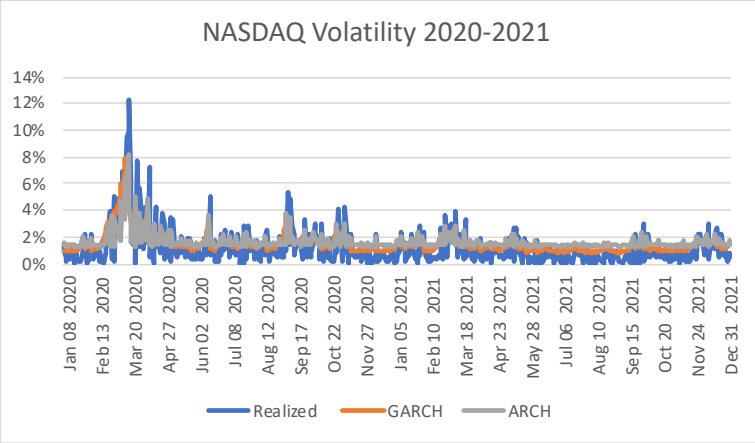
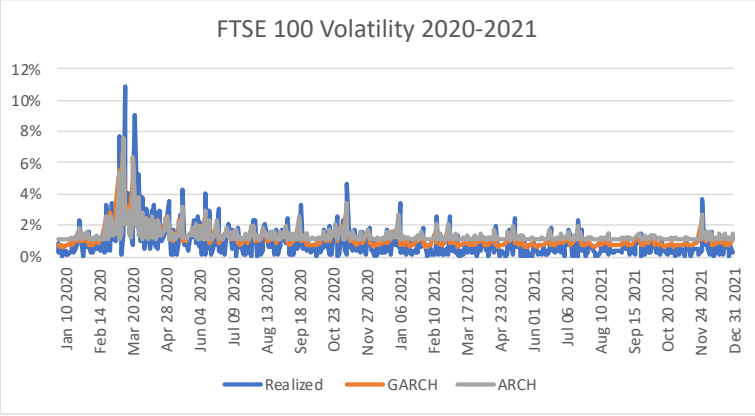


Figure 8 FTSE 100 Volatility 2020-2021



The DAX 30 index (Figure 10) also features its highest point of realized volatility on the same day as the CAC 40 index (Figure 9), with a difference of 94 basis points. Unlike the CAC 40 index, particularly the conditional volatility of the DAX 30 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 both conditional volatilities do not exceed 4%.

Another point to note is that none of the selected stocks from CAC 40 presented 0 in the parameters within two autoregressive models, unlike the stocks listed in DAX 30 such as SAP, Siemens, and BMW, that have an alpha coefficient of 0 in the ARCH model. Regarding the coefficients in the autoregressive models from DAX 30 index, 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 9 CAC 40 Volatility 2020-2021

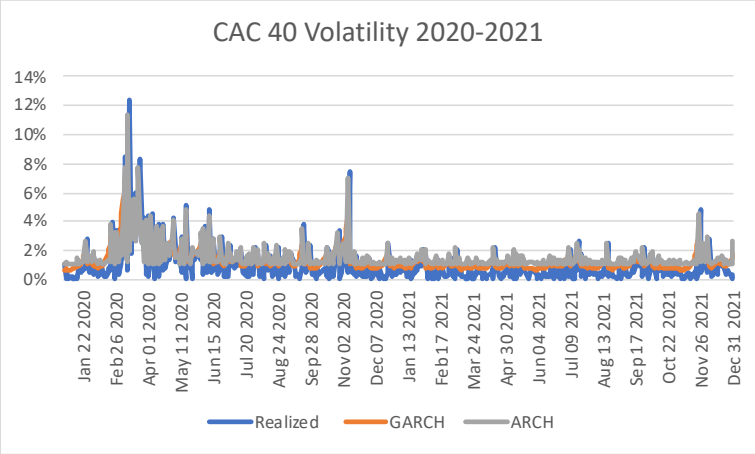


Figure 10 DAX 30 Volatility 2020-2021

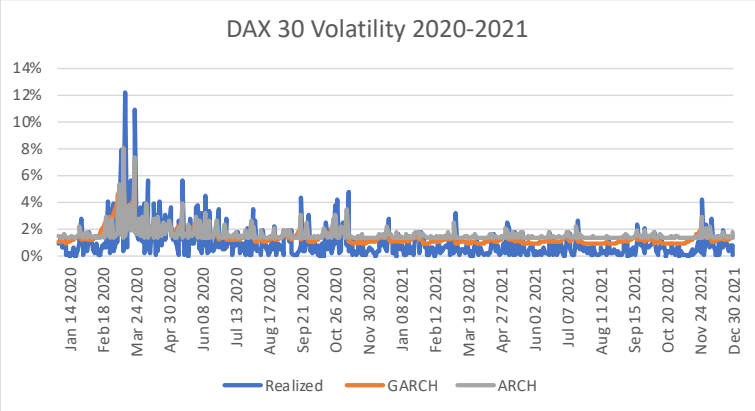
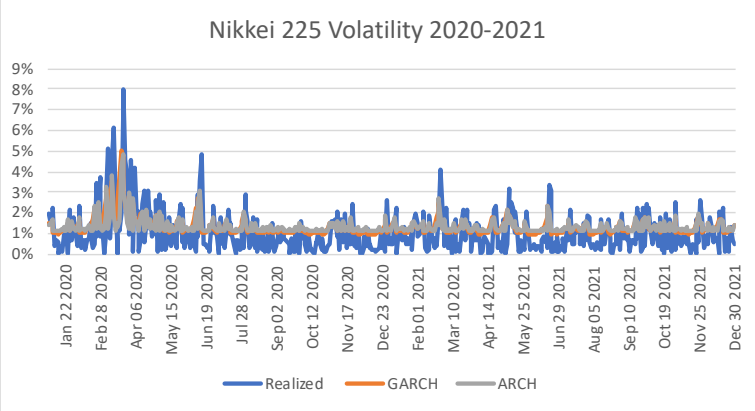


Figure 11 Nikkei 225 Volatility 2020-2021



The Nikkei 225 index (Figure 10) presents conglomerations of high volatility at the beginning of March, but it is not until March 23, 2020, when the conditional volatility in the ARCH model exceeds 5%. Unlike western indexes, 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 225 has lower volatility ranges compared to the other indexes, since this 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 indexes during the *Covid-19 period*.

Leaving aside the length of the Japanese index listing, the individual analysis of the thirty selected stocks shows that there were assets that increased the relationship between volatility to conditional variance and adjusted conditional variance, but there are companies such as Isuzu or Cyber agent that they even reduce the percentage of dependency compared to the period before the pandemic and according to the results of the GARCH model.

4.3 Critic of analysis models

Commonly analysts and academics, focus on the rate of return within a given period when they want to evaluate a stock. This scientific research sought to go beyond those boundaries and demonstrate the performance by period or year, it can give us inaccurate conclusions and expectations if we do not consider the frequency of the rate of return of the actions. Somehow the CAPM and Jensen Alpha findings are supplemented by the GARCH and ARCH findings.

Before the pandemic, most of the selected stocks of Nasdaq 100, FTSE 100, and CAC 40, performed better than expected; while most of the selected stocks of DAX 30 and Nikkei 225 behaved almost at the same level as expected. Surprisingly, there is a coincidence with the results of ARCH and GARCH, that shows that the volatility of the NASDAQ 100, FTSE 100 and CAC40 shares depended to a greater extent on the conditional variance and the adjusted conditional variance during the *Pre-Covid -19 period*, while DAX 30 and Nikkei 225 volatility had lower ARCH and GARCH coefficients.

This coincidence does not appear in the results of the *Covid-19 period*. Starting with the fact of the increase in the underperformance of selected stocks in each index, and an increase in the heterogeneity of performance that even occurs within the sectors of each index. This heterogeneity is presented through the results of GARCH and ARCH, where the volatility of the stocks was more variable and the dependence on the conditional variance and the adjusted conditional variance was not uniform by index during the pandemic.

Specifically, we can say that the “homogeneity” of the performance of the selected stocks in each index was lost in the *Covid-19 period*. While most stocks reduced their rate of return in the *Covid-19 period*, some stocks dramatically increased their rate of return during the pandemic. These stocks may be attractive to invest in, but investor’s decision can be made by looking at their

volatility over that period. The levels of volatility reached in the *Covid-19 period* cannot be generalized by index or even by sector at the moment, this assumption opens the possibility for a future study to find the variables that explain the lack of homogeneity of the rates of return, and of the levels of conditional volatility and adjusted conditional volatility during the *Covid-19 period*.

5 Conclusion and Discussion

To conclude, it is reiterated that this is only a general investigation of the dynamics of return, risk, and volatility of the stock markets before and during the Covid-19 pandemic. This text differs from current literature on three key points; first, by analyzing the performance of five of the world's most important indexes and skewing the listed stocks in order to obtain similar sample groups; second, evaluating the performance of the companies based on their return and risk through the CAPM and Jensen's Alpha indicators, and analyzing the non-constant daily volatility based on the ARCH and GARCH models; third, by making a comparative and descriptive cross-country analysis of two study periods.

In this chapter, we present a summary of the key findings of the investigation and seek to answer the research questions. A discussion of the results obtained is given in each answer of the correspond questions; and the limitations and recommendations are presented at the end of the section.

1.-What are the return dynamics of the shares under study before and during the Covid-19 pandemic?

According to the results found in CAPM and Jensen's Alpha, we can say that the performance of the stocks, although it was not constant before the pandemic, it was similar or even higher than expected. The average annual rate of return of each index is varied, with the Nikkei registering the highest rate of return during the five years prior to the pandemic; it is followed by DAX 30, Nasdaq 100, CAC 40, and FTSE 100 respectively by a significant difference between their average annual rate of return.

The order of the average annual rate of return changed in the pandemic; most of the selected stocks of Nasdaq100 increased their annual rate, and some even reached higher rates than expected; it is noteworthy that the stocks of the Travel and Accommodation sector and Communication services sector did not reach the expected rates, but they did not register negative annual returns. The average annual rate of return rating is followed by an increase from DAX 30 and a decrease from CAC 40. More than half of the stocks in both European indexes underperformed and unlike the Nasdaq 100 index, there are stocks that registered negative annual rates of return. Stocks belonging to the FTSE 100 that already underperformed before the pandemic, failed to improve after the onset of the Covid-19 crisis and other stocks joined this trend of underperformance and negative annual rates of return. This postulate can be supported by the decrease in the average annual rate of return of the index, which fell to 5,9%. Finally, the Nikkei 225 stocks were nowhere near of maintaining an expected annual rate of return and only four stocks managed to beat expectations, and the average annual rate of return was just 2,7%.

It can be concluded that the return dynamics changed during the *Covid-19 period*, in the sense that the order in which the indexes performed was different in the two periods studied. Except for the Nasdaq 100, the results obtained show that the rates of return were negatively affected during the Covid-19 crisis.

What are the risk dynamics of the stocks under study before and during the Covid-19 pandemic?

The calculations of each financial risk and their descriptive analysis allow us to answer this question. Before the pandemic, the average total risk, systematic risk, and unsystematic risk of Nikkei 225 was the highest among all indexes; and except for the French index, the average systematic risk was lower than the average unsystematic risk. During the *Covid-19 period*, Nasdaq 100, FTSE 100, CAC 40, and DAX 30 increased their average total risk and average systematic risk, while their average unsystematic risk decreased to a small extent. Nikkei 225 behaved in an almost contrary way, as its average total risk and average systematic risk diminished, its systematic risk raised. The expand of systematic risk in certain sectors in each index is also evident, such as in companies in the Information Technology sector in the Nasdaq 100 or in companies in the Energy Travel and Accommodation sector in the FTSE 100.

To conclude, it was found that the average of beta of the thirty selected stocks of each index, climbed during the Covid-19 crisis. Even thought, this increase was not significant for any of the indexes according to the results of the Beta paired samples T-test.

To what extent is the daily volatility of the stock markets affected by the conditional variance and by the adjusted conditional variance before and during the Covid-19 pandemic?

At first glance, the results obtained show that the volatility of the stock markets in the five years prior to the pandemic was not homogeneous in all the selected indexes and stocks. In addition, it was found that the periods of high volatility differ between the indexes and between the stocks selected in the corresponding index. On the other hand, the ARCH and GARCH models revealed that volatility is influenced by the variance of a previous day and the adjusted conditional variance during the *Pre-Covid-19 period*, and it is the Nasdaq 100 and FTSE 100 indexes that had coefficients ARCH and GARCH more.

On the other side, the ARCH and GARCH models show higher parameters during the Covid-19 crisis. From what can be said that volatility is much more affected by the previous variance and the conditional variance than before the pandemic. Even the conditional volatility of the ARCH model becomes higher than the realized volatility in days before the stock market crash. Unlike the previous period, the indexes and the selected stocks behave in a similar way with slight differences in the levels of volatility reached and differences in the days in which they reached their maximum volatility point. It can be said that the European indexes reacted first, followed by the Nasdaq 100 and finally the Nikkei 225, which registered its highest point of volatility until March 23, 2020.

The data obtained on volatility through the ARCH and GARCH models also show that the rapid and unexpected decline in the indexes in March 2020 was offset by a rapid recovery; since the volatility of the indexes and stocks, was stabilized in the first five months of the *Covid-19 period* and even the volatility came to decrease significantly at the end of 2020. In the year 2021 it is observed increases in volatility in both indexes and stocks, despite this fact there are no high peaks or points in which the realized volatility is exceeded by the conditional volatility or the adjusted conditional volatility**.**

5.1 Limitations and Recommendations

The limitations of this research lie mainly in the fact that it sought to give a synthesized result of each index, so it was not possible to inquire at the national or business level and thus be able to give explanations related to economic policies, decisions taken or events in the countries to which indexes and stocks belong. Therefore, this study can be used as a reference for the individual study of the indexes based on the search for the determining variables of the return variations during the Covid-19 crisis; likewise, another research can be carried out to determine which sectors were most volatile during the pandemic; or in which sectors it is advisable to invest after the breakdown caused by the Covid-19 virus based on a forecasting of return, risk and volatility.

Another limitation was the difference in years that made up each study period. In the *Pre-Covid-19 period*, having five years of study, it was not possible to maintain a normal distribution of the data, additionally the time horizon affected the descriptive statistics, i.e., in the descriptive statistics of annual returns of each index, the means are affected in a way that there are many outliers. As a suggestion for a future study, smaller study periods with the same number of years or panel groups by year could be considered; it would be interesting to add a third period, and make a comparison between the *Pre-Covid-19 period*, the *Covid-19 period* and the *Post-Covid-19 period*, making use of the models applied in this study or other tools to analyze the behavior of the stock markets during the pointed periods.

Finally, it only remains to say that the stock markets are inherent in unexpected events such as the spread of a virus worldwide. Living in an interconnected world, the effects of Covid-19 on stock markets expanded rapidly as the virus spread around the world, marking this period in the Economic history as one of the world's greatest financial crises in the XXI century, but also giving an opportunity to all those interested to expand their research capabilities and respond to what has not yet been explained about the Covid-19 pandemic.

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Appendices

Appendix 1. Companies stock selection

Nasdaq100	Sector
Apple Inc (AAPL)	Information Technology
MICROSOFT (MSFT)	Information Technology
Alphabet Inc Class A (GOOGL)	Communication Services
Amazon.com Inc (AMZN)	Consumer Discretionary
Tesla Inc (TSLA)	Automotive sector
Meta Platforms Inc (FB)	Communication Services
PepsiCo Inc (PEP)	Consumer Staples
Costco Wholesale Corp (COST)	Consumer Staples
T-Mobile US Inc (TMUS)	Communication Services
Booking Holdings Inc (BKNG)	Travel and acommodation services
MercadoLibre Inc (MELI)	Consumer Discretionary
Marriott International Inc (MAR)	Travel and acommodation services
Marvell Technology Group Ltd (MRVL)	Information Technology
Baidu Inc (BIDU)	Communication Services
KLA-Tencor Corporation (KLAC)	Information Technology
Keurig Dr Pepper Inc (KDP)	Consumer Staples
Illumina Inc (ILMN)	Healthcare
NetEase Inc (NTES)	Communication Services
American Electric Power Company Inc (AEP)	Utilities
Walgreens Boots Alliance Inc (WBA)	Consumer Staples
Xcel Energy Inc (XEL)	Utilities
Ross Stores Inc (ROST)	Consumer Discretionary
Dollar Tree Inc (DLTR)	Consumer Discretionary
PCAR Historical Data	Industrials
Copart Inc (CPRT)	Industrials
ANSYS Inc (ANSS)	Information Technology
Okta Inc (OKTA)	Information Technology
Sirius XM Holding Inc (SIRI)	Communication Services
Seagen Inc (SGEN)	Healthcare
DocuSign Inc (DOCU)	Information Technology
FTSE 100	**Sector**
Samsung Electronics Co Ltd DRC (0593xq)	Information Technology
Shell PLC (SHEL)	Energy
AstraZeneca PLC (AZN)	Healthcare
HSBC Holdings PLC (HSBA)	Financial
Unilever PLC (ULVR)	Consumer Staples
Rio Tinto PLC (RIO)	Materials
Diageo PLC (DGE)	Consumer Staples

GlaxoSmithKline PLC (GSK)	Healthcare
BP PLC (BP)	Energy
British American Tobacco PLC (BATS)	Consumer Staples
Rolls-Royce Holdings PLC (RR)	Automotive sector
Bunzl PLC (BNZL)	Industrials
InterContinental Hotels Group PLC (IHG)	Travel and acommodation services
Rentokil Initial PLC (RTO)	Industrials
Mondi PLC (MNDI)	Materials
Admiral Group PLC (ADML)	Financial
Schroders PLC (SDR)	Financial
Next PLC (NXT)	Consumer Discretionary
Halma PLC (HLMA)	Information Technology
.Spirax-Sarco Engineering PLC (SPX)	Industrials
Fresnillo PLC (FRES)	Industrials
DS Smith PLC (SMDS)	Materials
EasyJet PLC (EZJ)	Travel and acommodation services
ITV PLC (ITV)	Communication Services
Hikma Pharmaceuticals PLC (HIK)	Healthcare
Centrica PLC (CNA)	Utilities
Abrdn PLC (ABDN)	Financial
Berkeley Group Holdings PLC (BKGH)	Consumer Discretionary
Johnson Matthey PLC (JMAT)	Materials
Tui AG NA (TUIT)	Travel and acommodation services
CAC40	**Sector**
LVMH Moet Hennessy Louis Vuitton SE (LVMH)	Consumer Discretionary
L'Oreal SA (OREP)	Consumer Staples
TotalEnergies SE (TTEF)	Energy
Hermes International SCA (HRMS)	Consumer Discretionary
Sanofi SA (SASY)	Consumer Discretionary
Schneider Electric SE (SCHN)	Industrials
Airbus Group SE (AIR)	Industrials
AXA SA (AXAF)	Financial
Air Liquide SA (AIRP)	Materials
BNP Paribas SA (BNPP)	Financial
Dassault Systemes SE (DAST)	Information Technology
Vinci SA (SGEF)	Industrials
Pernod Ricard SA (PERP)	Consumer Staples
Capgemini SE (CAPP)	Information Technology
Safran SA (SAF)	Industrials
Danone SA (DANO)	Consumer Staples
STMicroelectronics NV (STM)	Information Technology
Compagnie de Saint Gobain SA (SGOB)	Industrials
Orange SA (ORAN)	Communication Services

Engie SA (ENGIE)	Utilities
Thales (TCFP)	Industrials
Compagnie Generale des Etablissements Michelin SCA (MICP)	Automobilistic sector
Legrand SA (LEGD)	Industrials
Veolia Environnement VE SA (VIE)	Utilities
Teleperformance SE (TEPRF)	Industrials
Eurofins Scientific SE (EUFI)	Healthcare
Publicis Groupe SA (PUBP)	Communication Services
Carrefour SA (CARR)	Consumer Staples
Bouygues SA (BOUY)	Industrials
Renault SA (RENA)	Automobilistic sector
DAX 30	**Sector**
SAP SE (SAPG)	Information Technology
Siemens AG Class N (SIEGn)	Industrials
Airbus Group SE (AIRG)	Industrials
Volkswagen AG VZO O,N, (VOWG_p)	Automobilistic sector
Deutsche Telekom AG Na (DTEGn)	Consumer Staples
Merck KGaA (MRCG)	Healthcare
Mercedes Benz Group AG (MBGn)	Automobiles
Deutsche Post AG NA O,N, (DPWGn)	Industrials
BASF SE NA O,N, (BASFn)	Materials
Bayerische Motoren Werke AG (BMWG)	Automobiles
Bayer AG NA (BAYGn)	Healthcare
Infineon Technologies AG NA O,N, (IFXGn)	Information Technology
Adidas AG (ADSGn)	Consumer Discretionary
Vonovia SE (VNAn)	Real Estate
5,-Muench, Rueckvers, VNA O,N, (MUVGn)	Financial
E,ON SE (EONGn)	Utilities
Henkel & Co KGaA AG Pref (HNKG_p)	Consumer Staples
Sartorius AG VZO O,N, (SATG_p)	Consumer Staples
Deutsche Boerse AG (DB1Gn)	Financial
Porsche Automobil Holding SE (PSHG_p)	Automobiles
Symrise AG Inh, O,N, (SY1G)	Materials
Heidelbergcement AG O,N, Company Profile	Materials
Zalando SE (ZALG)	Consumer Discretionary
Allianz SE VNA O,N, (ALVG)	Financial
Puma SE (PUMG)	Consumer Discretionary
MTU Aero Engines NA O,N, (MTXGn)	Industrials
Brenntag AG (BNRGn)	Industrials
Qiagen NV (QIA)	Healthcare
Covestro AG (1COV)	Materials
HelloFresh SE (HFGG)	Consumer Staples
Nikkei 225	**Sector**

NEC Corp, (6701)	Information Technology
Mitsubishi Heavy Industries Ltd, (7011)	Industrials
Dentsu Inc, (4324)	Communication Services
Isuzu Motors Ltd, (7202)	Automobilistic sector
ANA Holdings Inc (9202)	Travel and acommodation services
Daiwa Securities Group Inc, (8601)	Financial
Toray Industries Inc, (3402)	Materials
Minebea Mitsumi Inc (6479)	Industrials
AGC Inc (5201)	Communication Services
Meiji Holdings Co, Ltd, (2269)	Consumer Staples
CyberAgent Inc (4751)	Healthcare
Ricoh Co, Ltd, (7752)	Information Technology
Tokyo Electric Power Co, Inc, (9501)	Utilities
Hitachi Construction Machinery Co (6305)	Industrials
Tobu Railway Co, Ltd, (9001)	Industrials
Tosoh Corp, (4042)	Materials
Mazda Motor Corp (7261)	Automobiles
Nisshin Seifun Group Inc, (2002)	Consumer Staples
Sumitomo Dainippon Pharma Co Ltd (4506)	Healthcare
Haseko Corp (1808)	Consumer Discretionary
DeNA Co Ltd (2432)	Communication Services
Credit Saison Co, Ltd, (8253)	Financial
Ube Industries Ltd, (4208)	Materials
Takashimaya Co, Ltd, (8233)	Consumer Discretionary
Maruha Nichiro Corp (1333)	Consumer Staples
Nippon Light Metal Holdings Co, (5703)	Materials
Chiyoda Corp, (6366)	Industrials
Oki Electric Industry Co, Ltd, (6703)	Information Technology
Mitsui Engineering & Shipbuilding (7003)	Industrials
Unitika Ltd, (3103)	Consumer Discretionary

Appendix 2. *Pre-Covid- 19 period* 2015-2019 Calculations

Nasdaq 100	Realized annual return	Expected anual return	Jensen's Alpha	Total risk	Systematic risk	Unsystematic risk	Beta
Apple Inc (AAPL)	0,255	0,189	0,065	0,249	0,190	0,059	1,109
MICROSOFT (MSFT)	0,313	0,192	0,120	0,233	0,193	0,040	1,128
Alphabet Inc Class A (GOOGL)	0,238	0,185	0,053	0,238	0,185	0,053	1,081
Amazon.com Inc (AMZN)	0,491	0,211	0,280	0,292	0,214	0,078	1,250
Tesla Inc (TSLA)	0,255	0,189	0,066	0,449	0,189	0,260	1,105
Meta Platforms Inc (FB)	0,263	0,191	0,072	0,282	0,192	0,090	1,121
PepsiCo Inc (PEP)	0,088	0,056	0,032	0,146	0,038	0,108	0,220
Costco Wholesale Corp (COST)	0,186	0,104	0,082	0,187	0,092	0,095	0,540
T-Mobile US Inc (TMUS)	0,277	0,128	0,149	0,248	0,120	0,128	0,700
Booking Holdings Inc (BKNG)	0,163	0,157	0,006	0,257	0,153	0,104	0,895
MercadoLibre Inc (MELI)	0,469	0,211	0,258	0,414	0,214	0,200	1,251
Marriott International Inc (MAR)	0,174	0,152	0,023	0,235	0,147	0,089	0,857
Marvell Technology Group Ltd (MRVL)	0,199	0,181	0,018	0,348	0,181	0,167	1,056
Baidu Inc (BIDU)	-0,056	0,184	-0,240	0,347	0,184	0,163	1,074
KLA-Tencor Corporation (KLAC)	0,258	0,181	0,077	0,296	0,181	0,115	1,056
Keurig Dr Pepper Inc (KDP)	0,024	0,059	-0,035	0,436	0,041	0,395	0,240
Illumina Inc (ILMN)	0,210	0,198	0,012	0,378	0,200	0,178	1,165
NetEase Inc (NTES)	0,356	0,175	0,181	0,390	0,173	0,217	1,012
American Electric Power Company Inc (AEP)	-0,010	0,029	-0,038	0,298	0,007	0,291	0,039
Walgreens Boots Alliance Inc (WBA)	-0,021	0,126	-0,147	0,246	0,118	0,128	0,687
Xcel Energy Inc (XEL)	-0,017	0,028	-0,045	0,360	0,006	0,354	0,035
Ross Stores Inc (ROST)	0,233	0,121	0,112	0,240	0,112	0,127	0,657
Dollar Tree Inc (DLTR)	0,105	0,104	0,002	0,287	0,092	0,195	0,539
PCAR Historical Data	0,067	0,138	-0,071	0,239	0,132	0,107	0,768
Copart Inc (CPRT)	0,278	0,121	0,157	0,314	0,112	0,202	0,653
ANSYS Inc (ANSS)	0,290	0,161	0,129	0,225	0,157	0,068	0,919
Okta Inc (OKTA)	0,275	0,224	0,051	0,604	0,229	0,375	1,337
Sirius XM Holding Inc (SIRI)	0,181	0,124	0,057	0,214	0,115	0,099	0,674
Seagen Inc (SGEN)	0,418	0,190	0,228	0,437	0,191	0,246	1,114
DocuSign Inc (DOCU)	0,080	0,168	-0,088	0,388	0,166	0,223	0,968
FTSE 100	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
Samsung Electronics Co Ltd DRC (0593xq)	0,191	0,033	0,158	0,280	0,111	0,169	0,802

Shell PLC (SHEL)	0,035	0,043	-0,008	0,232	0,165	0,066	1,199
AstraZeneca PLC (AZN)	0,138	0,034	0,104	0,232	0,117	0,115	0,848
HSBC Holdings PLC (HSBA)	0,015	0,040	-0,025	0,202	0,148	0,054	1,070
Unilever PLC (ULVR)	0,127	0,032	0,095	0,196	0,106	0,090	0,769
Rio Tinto PLC (RIO)	0,140	0,047	0,093	0,316	0,189	0,128	1,366
Diageo PLC (DGE)	0,132	0,031	0,101	0,172	0,101	0,072	0,731
GlaxoSmithKline PLC (GSK)	0,074	0,034	0,040	0,186	0,117	0,069	0,849
BP PLC (BP)	0,057	0,043	0,014	0,238	0,168	0,070	1,219
British American Tobacco PLC (BATS)	0,012	0,035	-0,023	0,235	0,123	0,112	0,892
Rolls-Royce Holdings PLC (RR)	-0,119	0,040	-0,159	0,426	0,141	0,285	1,018
Bunzl PLC (BNZL)	0,049	0,033	0,016	0,183	0,107	0,076	0,775
InterContinental Hotels Group PLC (IHG)	0,175	0,039	0,137	0,217	0,136	0,081	0,988
Rentokil Initial PLC (RTO)	0,326	0,032	0,295	0,199	0,098	0,100	0,712
Mondi PLC (MNDI)	0,147	0,044	0,104	0,257	0,162	0,095	1,174
Admiral Group PLC (ADML)	0,156	0,033	0,123	0,206	0,103	0,103	0,746
Schroders PLC (SDR)	0,076	0,046	0,030	0,245	0,174	0,071	1,258
Next PLC (NXT)	0,055	0,031	0,023	0,286	0,097	0,189	0,706
Halma PLC (HLMA)	0,277	0,034	0,243	0,201	0,111	0,090	0,801
Spirax-Sarco Engineering PLC (SPX)	0,282	0,035	0,246	0,217	0,117	0,100	0,849
Fresnillo PLC (FRES)	0,047	0,029	0,018	0,403	0,083	0,320	0,601
DS Smith PLC (SMDS)	0,074	0,042	0,033	0,270	0,152	0,118	1,104
EasyJet PLC (EZJ)	-0,003	0,032	-0,036	0,351	0,103	0,248	0,745
ITV PLC (ITV)	-0,015	0,038	-0,053	0,288	0,133	0,155	0,960
Hikma Pharmaceuticals PLC (HIK)	0,064	0,033	0,030	0,347	0,107	0,239	0,778
Centrica PLC (CNA)	-0,169	0,037	-0,205	0,288	0,125	0,163	0,906
Abrdn PLC (ABDN)	-0,008	0,045	-0,053	0,268	0,167	0,101	1,212
Berkeley Group Holdings PLC (BKGH)	0,198	0,035	0,163	0,304	0,115	0,188	0,836
Johnson Matthey PLC (JMAT)	0,011	0,043	-0,032	0,264	0,157	0,107	1,136
Tui AG NA (TUIT)	0,023	0,038	-0,014	0,301	0,130	0,171	0,944
CAC 40	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
Moet Hennessy Louis Vuitton SE (LVMH)	0,293	0,097	0,196	0,252	0,197	0,055	1,170
L'Oreal SA (OREP)	0,157	0,073	0,084	0,199	0,145	0,054	0,862
TotalEnergies SE (TTEF)	0,055	0,083	-0,029	0,221	0,167	0,053	0,994
Hermes International SCA (HRMS)	0,198	0,063	0,135	0,199	0,124	0,075	0,735
Sanofi SA (SASY)	0,057	0,074	-0,017	0,210	0,147	0,063	0,872

Schneider Electric SE (SCHN)	0,116	0,095	0,021	0,239	0,192	0,047	1,142
Airbus Group SE (AIR)	0,299	0,096	0,203	0,266	0,195	0,071	1,161
AXA SA (AXAF)	0,088	0,095	-0,007	0,248	0,192	0,057	1,139
Air Liquide SA (AIRP)	0,069	0,079	-0,010	0,207	0,158	0,049	0,940
BNP Paribas SA (BNPP)	0,053	0,103	-0,050	0,273	0,210	0,063	1,251
Dassault Systemes SE (DAST)	0,267	0,067	0,200	0,231	0,132	0,098	0,786
Vinci SA (SGEF)	0,188	0,072	0,116	0,195	0,143	0,052	0,849
Pernod Ricard SA (PERP)	0,134	0,060	0,074	0,190	0,118	0,072	0,699
Capgemini SE (CAPP)	0,164	0,085	0,080	0,256	0,170	0,086	1,011
Safran SA (SAF)	0,249	0,081	0,168	0,235	0,162	0,073	0,962
Danone SA (DANO)	0,080	0,063	0,017	0,183	0,124	0,059	0,738
STMicroelectronics NV (STM)	0,402	0,103	0,298	0,377	0,211	0,166	1,251
Compagnie de Saint Gobain SA (SGOB)	0,037	0,094	-0,057	0,241	0,190	0,051	1,127
Orange SA (ORAN)	0,008	0,073	-0,065	0,215	0,145	0,070	0,861
Engie SA (ENGIE)	-0,034	0,075	-0,110	0,221	0,150	0,070	0,894
Thales (TCFP)	0,178	0,058	0,120	0,207	0,112	0,095	0,668
Compagnie Generale des Etablissements Michelin SCA (MICP)	0,106	0,075	0,031	0,237	0,150	0,087	0,891
Legrand SA (LEGD)	0,129	0,075	0,054	0,200	0,149	0,051	0,886
Veolia Environnement VE SA (VIE)	0,122	0,060	0,062	0,210	0,118	0,092	0,700
Teleperformance SE (TEPRF)	0,341	0,061	0,281	0,237	0,118	0,119	0,702
Eurofins Scientific SE (EUFI)	0,833	0,036	0,797	1,380	0,065	1,314	0,387
Publicis Groupe SA (PUBP)	-0,045	0,062	-0,107	0,246	0,121	0,126	0,717
Carrefour SA (CARR)	-0,069	0,073	-0,142	0,253	0,145	0,108	0,864
Bouygues SA (BOUY)	0,078	0,075	0,003	0,242	0,150	0,091	0,893
Renault SA (RENA)	-0,022	0,099	-0,122	0,311	0,202	0,108	1,203
DAX 30	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
SAP SE (SAPG)	0,182	0,072	0,111	0,214	0,160	0,054	0,912
Siemens AG Class N (SIEGn)	0,048	0,078	-0,030	0,220	0,176	0,044	1,000
Airbus	0,232	0,078	0,154	0,716	0,174	0,542	0,992
Volkswagen AG VZO O,N, (VOWG_p)	0,046	0,098	-0,052	0,326	0,220	0,106	1,256
Deutsche Telekom AG Na (DTEGn)	0,041	0,067	-0,026	0,205	0,148	0,056	0,845
Merck KGaA (MRCG)	0,086	0,061	0,025	0,219	0,136	0,083	0,775
Mercedes Benz Group AG (MBGn)	-0,034	0,093	-0,127	0,251	0,209	0,043	1,189
Deutsche Post AG NA O,N, (DPWGn)	0,072	0,073	-0,002	0,216	0,164	0,052	0,933

10,-BASF SE NA O,N, (BASFn)	0,018	0,085	-0,067	0,223	0,190	0,033	1,084
Bayerische Motoren Werke AG (BMWG)	-0,011	0,088	-0,099	0,245	0,197	0,047	1,125
Bayer AG NA (BAYGn)	-0,050	0,089	-0,139	0,270	0,200	0,070	1,139
Infineon Technologies AG NA O,N, (IFXGn)	0,240	0,095	0,145	0,314	0,213	0,101	1,216
Adidas AG (ADSGn)	0,426	0,063	0,363	0,257	0,140	0,117	0,796
Vonovia SE (VNAn)	0,136	0,045	0,091	0,219	0,099	0,120	0,564
Muench, Rueckvers, VNA O,N, (MUVGn)	0,114	0,057	0,057	0,178	0,127	0,051	0,722
E,ON SE (EONGn)	-0,037	0,071	-0,108	0,288	0,157	0,130	0,897
Henkel & Co KGaA AG Pref (HNKG_p)	0,027	0,056	-0,029	0,202	0,125	0,077	0,710
Sartorius AG VZO O,N, (SATG_p)	0,361	0,075	0,285	0,477	0,168	0,309	0,959
Deutsche Boerse AG (DB1Gn)	0,216	0,060	0,156	0,217	0,132	0,085	0,753
Porsche Automobil Holding SE (PSHG_p)	0,049	0,095	-0,046	0,311	0,214	0,097	1,218
Symrise AG Inh, O,N, (SY1G)	0,158	0,058	0,100	0,209	0,128	0,081	0,728
Heidelbergcement AG O,N, Company Profile	0,050	0,078	-0,028	0,241	0,175	0,066	0,997
Zalando SE (ZALG)	0,203	0,065	0,138	0,379	0,144	0,236	0,818
Allianz SE VNA O,N, (ALVG)	0,120	0,076	0,044	0,201	0,169	0,032	0,963
Puma SE (PUMG)	5,589	-0,050	5,639	3,944	-0,122	4,066	-0,694
MTU Aero Engines NA O,N, (MTXGn)	0,322	0,066	0,257	0,235	0,146	0,089	0,832
Brenntag AG (BNRGn)	0,036	0,067	-0,031	0,231	0,148	0,083	0,845
Qiagen NV (QIA)	0,138	0,061	0,077	0,277	0,136	0,141	0,773
Covestro AG (1COV)	0,064	0,079	-0,015	0,424	0,176	0,248	1,004
HelloFresh SE (HFGG)	0,021	0,083	-0,061	0,546	0,185	0,361	1,055
Nikkei 225	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
NEC Corp, (6701)	5,938	0,079	5,859	4,096	0,180	3,916	0,928
Mitsubishi Heavy Industries Ltd, (7011)	4,611	-0,073	4,684	3,933	-0,169	4,102	-0,871
Dentsu Inc, (4324)	-0,012	0,092	-0,104	0,315	0,209	0,105	1,078
Isuzu Motors Ltd, (7202)	0,023	0,099	-0,076	0,314	0,226	0,088	1,162
ANA Holdings Inc (9202)	0,063	0,057	0,007	0,206	0,129	0,076	0,666
Daiwa Securities Group Inc, (8601)	-0,074	0,087	-0,161	0,262	0,199	0,063	1,023
Toray Industries Inc, (3402)	-0,025	0,071	-0,096	0,245	0,163	0,082	0,837
Minebea Mitsumi Inc (6479)	0,137	0,115	0,022	0,402	0,263	0,139	1,352
AGC Inc (5201)	0,110	0,086	0,023	0,299	0,197	0,101	1,015
Meiji Holdings Co, Ltd, (2269)	0,104	0,057	0,047	0,278	0,129	0,149	0,663

CyberAgent Inc (4751)	0,206	0,076	0,130	0,401	0,174	0,227	0,894
Ricoh Co, Ltd, (7752)	0,037	0,071	-0,034	0,290	0,162	0,128	0,834
Tokyo Electric Power Co, Inc, (9501)	0,043	0,070	-0,027	0,327	0,160	0,167	0,825
Hitachi Construction Machinery Co (6305)	0,114	0,103	0,011	0,338	0,235	0,103	1,211
Tobu Railway Co, Ltd, (9001)	0,085	0,059	0,026	0,218	0,135	0,083	0,694
Tosoh Corp, (4042)	0,148	0,100	0,048	0,352	0,230	0,122	1,183
Mazda Motor Corp (7261)	-0,166	0,104	-0,270	0,324	0,238	0,087	1,223
Nisshin Seifun Group Inc, (2002)	0,142	0,069	0,073	0,252	0,157	0,096	0,807
Sumitomo Dainippon Pharma Co Ltd (4506)	0,211	0,077	0,133	0,367	0,177	0,191	0,909
Haseko Corp (1808)	0,145	0,090	0,055	0,319	0,205	0,114	1,054
DeNA Co Ltd (2432)	0,116	0,062	0,054	0,378	0,141	0,236	0,727
Credit Saison Co, Ltd, (8253)	0,007	0,086	-0,078	0,292	0,196	0,097	1,007
Ube Industries Ltd, (4208)	0,620	0,017	0,603	0,749	0,037	0,713	0,189
Takashimaya Co, Ltd, (8233)	-0,055	0,074	-0,129	0,270	0,168	0,101	0,866
Maruha Nichiro Corp (1333)	0,132	0,045	0,087	0,261	0,102	0,159	0,523
Nippon Light Metal Holdings Co, (5703)	6,111	0,059	6,052	4,116	0,134	3,982	0,690
Chiyoda Corp, (6366)	-0,148	0,082	-0,230	0,446	0,188	0,258	0,968
Oki Electric Industry Co, Ltd, (6703)	-0,043	0,073	-0,117	0,292	0,168	0,124	0,863
Mitsui Engineering & Shipbuilding (7003)	-0,102	0,088	-0,190	0,375	0,200	0,174	1,031
Unitika Ltd, (3103)	-0,040	0,086	-0,125	0,351	0,196	0,156	1,006

Appendix 3. *Covid-19 2020-2021 period* Calculations

Nasdaq 100	Realized annual return	Expected anual return	Jensen's Alpha	Total risk	Systematic risk	Unsystematic risk	Beta
Apple Inc (AAPL)	0,666	0,483	0,183	0,375	0,330	0,045	1,143
MICROSOFT (MSFT)	0,548	0,467	0,081	0,344	0,319	0,026	1,104
Alphabet Inc Class A (GOOGL)	0,547	0,402	0,145	0,322	0,273	0,049	0,946
Amazon,com Inc (AMZN)	0,413	0,365	0,049	0,322	0,247	0,075	0,855
Tesla Inc TSLA	3,659	0,618	3,041	0,743	0,426	0,317	1,477
Meta Platforms Inc (FB)	0,378	0,443	-0,065	0,386	0,302	0,084	1,045
PepsiCo Inc (PEP)	0,172	0,297	-0,125	0,279	0,199	0,080	0,691
Costco Wholesale Corp (COST)	0,431	0,255	0,176	0,246	0,170	0,076	0,589
T-Mobile US Inc (TMUS)	0,285	0,322	-0,036	0,334	0,217	0,118	0,751

Booking Holdings Inc (BKNG)	0,188	0,354	-0,166	0,438	0,239	0,198	0,830
MercadoLibre Inc (MELI)	0,764	0,501	0,264	0,530	0,353	0,178	1,219
Marriott International Inc (MAR)	0,195	0,299	-0,104	0,521	0,207	0,315	0,714
Marvell Technology Group Ltd (MRVL)	1,045	0,482	0,564	0,494	0,338	0,156	1,167
Baidu Inc (BIDU)	0,237	0,343	-0,106	0,516	0,238	0,278	0,822
KLA-Tencor Corporation (KLAC)	0,769	0,579	0,191	0,515	0,409	0,105	1,414
Keurig Dr Pepper Inc (KDP)	0,181	0,210	-0,030	0,304	0,141	0,163	0,487
Illumina Inc (ILMN)	0,162	0,359	-0,197	0,404	0,250	0,154	0,862
American Electric Power Company Inc (AEP)	0,014	0,204	-0,190	0,296	0,138	0,158	0,477
NetEase Inc (NTES)	0,443	0,329	0,114	0,478	0,228	0,250	0,789
Walgreens Boots Alliance Inc (WBA)	0,017	0,224	-0,207	0,396	0,153	0,243	0,528
Xcel Energy Inc (XEL)	0,083	0,252	-0,169	0,308	0,173	0,135	0,598
Ross Stores Inc (ROST)	0,101	0,338	-0,237	0,459	0,235	0,224	0,812
Dollar Tree Inc (DLTR)	0,334	0,254	0,079	0,421	0,172	0,248	0,595
PCAR Historical Data	0,108	0,256	-0,148	0,311	0,175	0,135	0,606
Copart Inc (CPRT)	0,375	0,354	0,021	0,356	0,246	0,109	0,850
ANSYS Inc (ANSS)	0,349	0,481	-0,133	0,395	0,338	0,057	1,167
Okta Inc (OKTA)	0,562	0,400	0,162	0,480	0,280	0,200	0,966
Sirius XM Holding Inc (SIRI)	0,007	0,304	-0,297	0,361	0,210	0,151	0,726
Seagen Inc (SGEN)	0,269	0,289	-0,020	0,420	0,198	0,223	0,683
DocuSign Inc (DOCU)	0,771	0,411	0,360	0,627	0,287	0,340	0,993
FTSE 100	**Realized annual return**	**Expected annual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
Samsung Electronics Co Ltd DRC (0593xq)	0,243	0,015	0,228	0,338	0,218	0,120	0,968
Shell PLC (SHEL)	-0,055	0,021	-0,076	0,452	0,358	0,095	1,585
AstraZeneca PLC (AZN)	0,109	0,010	0,098	0,276	0,116	0,160	0,514
HSBC Holdings PLC (HSBA)	-0,078	0,015	-0,093	0,338	0,226	0,112	1,001
Unilever PLC (ULVR)	-0,022	0,010	-0,032	0,231	0,112	0,119	0,496
Rio Tinto PLC (RIO)	0,115	0,017	0,098	0,367	0,254	0,113	1,126
Diageo PLC (DGE)	0,167	0,014	0,153	0,281	0,207	0,074	0,919
GlaxoSmithKline PLC (GSK)	-0,024	0,012	-0,036	0,236	0,147	0,089	0,651
BP PLC (BP)	-0,066	0,021	-0,088	0,465	0,364	0,101	1,614
British American Tobacco PLC (BATS)	-0,043	0,013	-0,057	0,278	0,183	0,095	0,812
Rolls-Royce Holdings PLC (RR)	-0,012	0,024	-0,036	0,803	0,421	0,382	1,868
Bunzl PLC (BNZL)	0,231	0,011	0,220	0,288	0,133	0,155	0,588
InterContinental Hotels Group PLC (IHG)	0,072	0,020	0,052	0,477	0,333	0,144	1,476
Rentokil Initial PLC (RTO)	0,202	0,012	0,190	0,341	0,158	0,184	0,698
Mondi PLC (MNDI)	0,065	0,016	0,049	0,311	0,242	0,069	1,073

Admiral Group PLC (ADML)	0,205	0,010	0,195	0,251	0,109	0,141	0,485
Schroders PLC (SDR)	0,096	0,017	0,079	0,342	0,260	0,082	1,151
Next PLC (NXT)	0,171	0,018	0,153	0,408	0,295	0,113	1,309
Halma PLC (HLMA)	0,277	0,013	0,265	0,280	0,165	0,115	0,730
Spirax-Sarco Engineering PLC (SPX)	0,391	0,012	0,379	0,272	0,151	0,121	0,669
Fresnillo PLC (FRES)	0,315	0,011	0,304	0,466	0,125	0,341	0,552
DS Smith PLC (SMDS)	0,062	0,015	0,047	0,350	0,227	0,123	1,006
EasyJet PLC (EZJ)	-0,128	0,023	-0,151	0,709	0,408	0,300	1,809
ITV PLC (ITV)	-0,042	0,017	-0,060	0,473	0,275	0,198	1,219
Hikma Pharmaceuticals PLC (HIK)	0,107	0,009	0,097	0,309	0,092	0,217	0,406
Centrica PLC (CNA)	-0,152	0,005	-0,157	0,316	0,001	0,315	0,004
Abrdn PLC (ABDN)	-0,055	0,021	-0,076	0,439	0,351	0,088	1,557
Berkeley Group Holdings PLC (BKGH)	0,050	0,015	0,036	0,337	0,211	0,126	0,937
Johnson Matthey PLC (JMAT)	-0,115	0,015	-0,130	0,363	0,230	0,133	1,017
Tui AG NA (TUIT)	-0,318	0,022	-0,340	0,820	0,377	0,442	1,671
CAC 40	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
LVMH Moet Hennessy Louis Vuitton SE (LVMH	0,380	0,131	0,249	0,307	0,258	0,049	1,038
L'Oreal SA (OREP)	0,290	0,090	0,201	0,250	0,177	0,074	0,710
TotalEnergies SE (TTEF)	0,032	0,161	-0,129	0,398	0,317	0,081	1,275
Hermes International SCA (HRMS)	0,559	0,093	0,466	0,267	0,183	0,084	0,736
Sanofi SA (SASY)	0,020	0,059	-0,040	0,224	0,118	0,107	0,473
Schneider Electric SE (SCHN)	0,430	0,128	0,302	0,308	0,252	0,056	1,013
Airbus Group SE (AIR)	0,091	0,217	-0,127	0,565	0,427	0,139	1,716
AXA SA (AXAF)	0,086	0,152	-0,065	0,354	0,298	0,056	1,200
Air Liquide SA (AIRP)	0,132	0,091	0,041	0,238	0,179	0,060	0,719
BNP Paribas SA (BNPP)	0,178	0,182	-0,004	0,437	0,358	0,079	1,440
Dassault Systemes SE (DAST)	0,390	0,075	0,314	0,303	0,151	0,153	0,599
Vinci SA (SGEF)	0,057	0,180	-0,123	0,415	0,357	0,058	1,419
Pernod Ricard SA (PERP)	0,179	0,079	0,100	0,228	0,158	0,071	0,626
Capgemini SE (CAPP)	0,481	0,122	0,359	0,344	0,244	0,101	0,968
Safran SA (SAF)	0,030	0,218	-0,187	0,547	0,433	0,114	1,719
Danone SA (DANO)	-0,111	0,066	-0,176	0,247	0,131	0,116	0,521
STMicroelectronics NV (STM)	0,471	0,158	0,313	0,436	0,315	0,121	1,250
Compagnie de Saint Gobain SA (SGOB)	0,391	0,149	0,242	0,376	0,296	0,080	1,176
Orange SA (ORAN)	-0,123	0,078	-0,201	0,252	0,156	0,096	0,619
Engie SA (ENGIE)	0,000	0,116	-0,117	0,312	0,232	0,080	0,921
Thales (TCFP)	-0,041	0,132	-0,172	0,354	0,262	0,092	1,040
Compagnie Generale des Etablissements Michelin SCA (MICP)	0,206	0,122	0,083	0,317	0,244	0,073	0,968

Legrand SA (LEGD)	0,238	0,109	0,129	0,293	0,218	0,076	0,865
Veolia Environnement VE SA (VIE)	0,253	0,118	0,135	0,335	0,235	0,100	0,932
Teleperformance SE (TEPRF)	0,413	0,083	0,329	0,337	0,166	0,171	0,659
Eurofins Scientific SE (EUFI)	0,571	0,046	0,525	0,366	0,093	0,273	0,369
Publicis Groupe SA (PUBP)	0,301	0,133	0,168	0,389	0,264	0,125	1,049
Carrefour SA (CARR)	0,089	0,069	0,020	0,313	0,138	0,175	0,548
Bouygues SA (BOUY)	-0,014	0,160	-0,174	0,389	0,318	0,071	1,264
Renault SA (RENA)	0,008	0,217	-0,209	0,574	0,432	0,142	1,716
DAX 30	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystem atic risk**	**Beta**
SAP SE (SAPG)	0,074	0,119	-0,045	0,319	0,234	0,085	0,921
Siemens AG Class N (SIEGn)	0,276	0,152	0,124	0,343	0,295	0,048	1,164
Airbus	0,081	0,197	-0,115	0,568	0,380	0,188	1,497
Volkswagen AG VZO O,N, (VOWG_p)	0,109	0,186	-0,077	0,448	0,359	0,089	1,416
Deutsche Telekom AG Na (DTEGn)	0,092	0,097	-0,006	0,252	0,191	0,061	0,754
Merck KGaA (MRCG)	0,520	0,082	0,438	0,277	0,162	0,114	0,640
Mercedes Benz Group AG (MBGn)	0,307	0,201	0,107	0,476	0,388	0,088	1,527
Deutsche Post AG NA O,N, (DPWGn)	0,353	0,125	0,229	0,319	0,244	0,076	0,961
10,-BASF SE NA O,N, (BASFn)	0,014	0,147	-0,133	0,337	0,286	0,051	1,126
Bayerische Motoren Werke AG (BMWG)	-0,137	0,148	-0,285	0,567	0,287	0,280	1,131
Bayer AG NA (BAYGn)	-0,145	0,125	-0,270	0,345	0,245	0,100	0,965
Infineon Technologies AG NA O,N, (IFXGn)	0,557	0,173	0,385	0,441	0,335	0,107	1,318
Adidas AG (ADSGn)	-0,003	0,130	-0,133	0,357	0,254	0,103	0,999
Vonovia SE (VNAn)	0,075	0,070	0,006	0,267	0,139	0,128	0,550
Muench, Rueckvers, VNA O,N, (MUVGn)	0,066	0,153	-0,087	0,373	0,298	0,075	1,172
E,ON SE (EONGn)	0,165	0,074	0,091	0,247	0,148	0,099	0,582
Henkel & Co KGaA AG Pref (HNKG_p)	-0,096	0,083	-0,179	0,232	0,164	0,068	0,646
Sartorius AG VZO O,N, (SATG_p)	0,899	0,045	0,854	0,395	0,093	0,302	0,366
Deutsche Boerse AG (DB1Gn)	0,065	0,099	-0,034	0,279	0,195	0,084	0,770
Porsche Automobil Holding SE (PSHG_p)	0,230	0,184	0,046	0,437	0,357	0,081	1,406
Symrise AG Inh, O,N, (SY1G)	0,209	0,048	0,161	0,234	0,099	0,136	0,389
Heidelbergcement AG O,N, Company Profile	0,028	0,148	-0,120	0,376	0,288	0,088	1,134
Zalando SE (ZALG)	0,356	0,090	0,265	0,400	0,179	0,221	0,705
Allianz SE VNA O,N, (ALVG)	0,032	0,148	-0,116	0,336	0,288	0,048	1,137

Puma SE (PUMG)	0,341	0,128	0,213	0,373	0,251	0,122	0,988
MTU Aero Engines NA O,N, (MTXGn)	-0,030	0,184	-0,214	0,536	0,357	0,180	1,406
Brenntag AG (BNRGn)	0,337	0,110	0,226	0,299	0,216	0,083	0,853
Qiagen NV (QIA)	0,309	0,011	0,298	0,263	0,028	0,235	0,112
Covestro AG (1COV)	0,218	0,133	0,085	0,356	0,259	0,097	1,022
HelloFresh SE (HFGG)	1,219	0,025	1,194	0,570	0,056	0,514	0,219
Nikkei 225	**Realized annual return**	**Expected anual return**	**Jensen's Alpha**	**Total risk**	**Systematic risk**	**Unsystematic risk**	**Beta**
NEC Corp, (6701)	0,154	0,105	0,049	0,347	0,175	0,172	0,776
Mitsubishi Heavy Industries Ltd, (7011)	-0,172	0,123	-0,295	0,327	0,205	0,122	0,907
Dentsu Inc, (4324)	0,146	0,179	-0,033	0,435	0,298	0,137	1,320
Isuzu Motors Ltd, (7202)	0,156	0,166	-0,011	0,440	0,277	0,162	1,230
ANA Holdings Inc (9202)	-0,119	0,097	-0,216	0,422	0,161	0,260	0,715
Daiwa Securities Group Inc, (8601)	0,133	0,111	0,023	0,292	0,184	0,108	0,816
Toray Industries Inc, (3402)	0,018	0,148	-0,130	0,351	0,247	0,105	1,093
Minebea Mitsumi Inc (6479)	0,285	0,168	0,117	0,360	0,280	0,080	1,241
AGC Inc (5201)	0,259	0,134	0,125	0,341	0,224	0,117	0,993
Meiji Holdings Co, Ltd, (2269)	-0,016	0,042	-0,058	0,210	0,070	0,140	0,312
CyberAgent Inc (4751)	0,570	0,091	0,479	0,430	0,151	0,278	0,670
Ricoh Co, Ltd, (7752)	0,044	0,136	-0,092	0,445	0,226	0,219	1,003
Tokyo Electric Power Co, Inc, (9501)	-0,146	0,093	-0,239	0,391	0,154	0,237	0,684
Hitachi Construction Machinery Co (6305)	0,085	0,157	-0,072	0,388	0,261	0,126	1,159
Tobu Railway Co, Ltd, (9001)	-0,153	0,087	-0,240	0,308	0,144	0,163	0,640
Tosoh Corp, (4042)	0,058	0,130	-0,073	0,326	0,217	0,109	0,962
Mazda Motor Corp (7261)	0,094	0,175	-0,081	0,493	0,291	0,202	1,290
Nisshin Seifun Group Inc, (2002)	-0,032	0,099	-0,131	0,281	0,165	0,116	0,731
Sumitomo Dainippon Pharma Co Ltd (4506)	-0,155	0,138	-0,293	0,393	0,229	0,163	1,017
Haseko Corp Company Profile	0,028	0,117	-0,089	0,297	0,195	0,102	0,865
DeNA Co Ltd (2432)	0,084	0,094	-0,010	0,394	0,157	0,237	0,696
Credit Saison Co, Ltd, (8253)	-0,147	0,144	-0,291	0,389	0,240	0,149	1,063
Ube Industries Ltd, (4208)	-0,046	0,116	-0,162	0,295	0,193	0,102	0,857
Takashimaya Co, Ltd, (8233)	-0,006	0,100	-0,106	0,362	0,166	0,196	0,738
Maruha Nichiro Corp (1333)	-0,038	0,089	-0,127	0,281	0,148	0,133	0,656
Nippon Light Metal Holdings Co, (5703)	-0,098	0,127	-0,225	0,345	0,212	0,133	0,940
Chiyoda Corp, (6366)	0,272	0,133	0,139	0,508	0,222	0,287	0,982

Oki Electric Industry Co, Ltd, (6703)	-0,193	0,119	-0,311	0,329	0,198	0,131	0,876
Mitsui Engineering & Shipbuilding (7003)	-0,232	0,202	-0,434	0,591	0,337	0,254	1,494
Unitika Ltd, (3103)	-0,015	0,138	-0,153	0,459	0,229	0,230	1,016

Appendix 4. *Pre-Covid- 19 period* 2015-2019 Volatility coefficients

	ARCH		GARCH		
	ω	α_1	ω	α_1	β_1
Nasdaq 100	0,00008	0,33615	0,00002	0,23702	0,60187
Apple Inc (AAPL)	0,00018	0,31011	0,00004	0,23863	0,58816
MICROSOFT (MSFT)	0,00016	0,25246	0,00008	0,25135	0,41603
Alphabet Inc Class A (GOOGL)	0,00020	0,10653	0,00008	0,21763	0,50957
Amazon.com Inc (AMZN)	0,00025	0,33301	0,00006	0,33257	0,57164
Tesla Inc (TSLA)	0,00072	0,09854	0,00030	0,15629	0,49698
Meta Platforms Inc (FB)	0,00028	0,14533	0,00007	0,14046	0,63266
PepsiCo Inc (PEP)	0,00007	0,18862	0,00003	0,16474	0,45274
Costco Wholesale Corp (COST)	0,00010	0,38440	0,00007	0,39115	0,24428
T-Mobile US Inc (TMUS)	0,00021	0,15929	0,00010	0,23390	0,39254
Booking Holdings Inc (BKNG)	0,00023	0,16348	0,00013	0,24560	0,31862
MercadoLibre Inc (MELI)	0,00065	0,05685	0,00025	0,18228	0,49788
Marriott International Inc (MAR)	0,00018	0,17405	0,00002	0,12258	0,78949
Marvell Technology Group Ltd (MRVL)	0,00047	0,03191	0,00031	0,05246	0,31901
Baidu Inc (BIDU)	0,00038	0,23068	0,00016	0,23357	0,46488
KLA-Tencor Corporation (KLAC)	0,00030	0,16993	0,00016	0,26408	0,35257
Keurig Dr Pepper Inc (KDP)	0,00075	0,00000	0,00075	0,00000	0,00000
Illumina Inc (ILMN)	0,00052	0,11659	0,00030	0,15840	0,35010
NetEase Inc (NTES)	0,00057	0,05212	0,00037	0,06814	0,32352
American Electric Power Company Inc (AEP)	0,00035	0,00000	0,00012	0,40542	0,52139
Walgreens Boots Alliance Inc (WBA)	0,00019	0,24737	0,00011	0,24431	0,34840
Xcel Energy Inc (XEL)	0,00051	0,00000	0,00051	0,00000	0,00000
Ross Stores Inc (ROST)	0,00021	0,09147	0,00011	0,09296	0,41557
Dollar Tree Inc (DLTR)	0,00026	0,32912	0,00025	0,29518	0,00000
PCAR Historical Data	0,00019	0,17648	0,00012	0,17490	0,29200
Copart Inc (CPRT)	0,00039	0,00000	0,00031	0,42504	0,04894
ANSYS Inc (ANSS)	0,00017	0,14062	0,00005	0,18138	0,61259
Okta Inc (OKTA)	0,00145	0,00000	0,00145	0,00000	0,00000
Sirius XM Holding Inc (SIRI)	0,00018	0,00000	0,00001	0,03720	0,92023
Seagen Inc (SGEN)	0,00075	0,01317	0,00048	0,02290	0,34063
DocuSign Inc (DOCU)	0,00031	0,95556	0,00005	0,25999	0,68679
FTSE 100	5,35E-05	2,91E-01	1,12E-05	2,81E-01	6,13E-01
Samsung Electronics Co Ltd DRC (0593xq)	3,06E-04	1,22E-02	2,98E-04	2,01E-02	1,67E-02

Shell PLC (SHEL)	1,63E-04	2,58E-01	3,34E-05	1,92E-01	6,72E-01
AstraZeneca PLC (AZN)	1,73E-04	2,16E-01	9,35E-05	2,29E-01	3,61E-01
HSBC Holdings PLC (HSBA)	1,34E-04	1,79E-01	2,24E-05	9,99E-02	7,60E-01
Unilever PLC (ULVR)	1,22E-04	1,66E-01	8,91E-05	2,01E-01	2,31E-01
Rio Tinto PLC (RIO)	3,67E-04	7,41E-02	1,64E-04	1,18E-01	4,64E-01
Diageo PLC (DGE)	1,01E-04	1,48E-01	7,42E-05	1,38E-01	2,33E-01
GlaxoSmithKline PLC (GSK)	1,16E-04	1,65E-01	4,61E-05	1,63E-01	5,06E-01
BP PLC (BP)	1,94E-04	1,40E-01	5,03E-05	2,11E-01	5,80E-01
British American Tobacco PLC (BATS)	1,75E-04	2,07E-01	9,02E-05	1,99E-01	4,03E-01
Rolls-Royce Holdings PLC (RR)	7,19E-04	0,00E+00	2,35E-04	5,43E-01	4,55E-01
Bunzl PLC (BNZL)	9,87E-05	2,86E-01	9,58E-05	2,94E-01	7,79E-03
InterContinental Hotels Group PLC (IHG)	1,43E-04	2,69E-01	5,88E-05	1,21E-01	5,23E-01
Rentokil Initial PLC (RTO)	1,20E-04	2,51E-01	4,62E-05	2,09E-01	5,39E-01
Mondi PLC (MNDI)	2,31E-04	1,28E-01	5,50E-05	1,03E-01	6,77E-01
Admiral Group PLC (ADML)	1,22E-04	3,15E-01	1,14E-04	3,36E-01	4,36E-02
Schroders PLC (SDR)	1,55E-04	3,32E-01	5,07E-05	2,67E-01	5,01E-01
Next PLC (NXT)	2,87E-04	1,14E-01	2,24E-04	1,13E-01	2,02E-01
Halma PLC (HLMA)	1,27E-04	2,44E-01	6,23E-05	1,71E-01	4,37E-01
Spirax-Sarco Engineering PLC (SPX)	1,49E-04	2,38E-01	5,08E-05	3,57E-01	4,15E-01
Fresnillo PLC (FRES)	4,88E-04	2,41E-01	3,34E-04	2,10E-01	2,70E-01
DS Smith PLC (SMDS)	2,31E-04	1,92E-01	9,97E-05	1,70E-01	4,83E-01
EasyJet PLC (EZJ)	3,94E-04	1,99E-01	2,82E-04	2,02E-01	2,38E-01
ITV PLC (ITV)	2,25E-04	2,52E-01	3,28E-04	0,00E+00	0,00E+00
Hikma Pharmaceuticals PLC (HIK)	3,56E-04	2,79E-01	3,42E-04	2,77E-01	3,12E-02
Centrica PLC (CNA)	2,24E-04	4,77E-01	3,29E-04	2,29E-01	0,00E+00
Abrdn PLC (ABDN)	2,03E-04	2,87E-01	2,86E-04	1,72E-01	0,00E+00
Berkeley Group Holdings PLC (BKGH)	2,67E-04	2,62E-01	8,73E-05	3,50E-01	4,90E-01
Johnson Matthey PLC (JMAT)	2,03E-04	3,02E-01	6,45E-05	2,78E-01	5,12E-01
Tui AG NA (TUIT)	2,42E-04	3,52E-01	6,68E-05	2,53E-01	5,96E-01
CAC 40	0,000081	0,281490	0,000025	0,194424	0,580443
Moet Hennessy Louis Vuitton SE (LVMH)	0,000211	0,172828	0,000093	0,157439	0,481133
L'Oreal SA (OREP)	0,000134	0,158084	0,000045	0,204824	0,550834
TotalEnergies SE (TTEF)	0,000155	0,199796	0,000021	0,188792	0,723998
Hermes International SCA (HRMS)	0,000136	0,151937	0,000098	0,192172	0,206949
Sanofi SA (SASY)	0,000150	0,144933	0,000037	0,093171	0,695972
Schneider Electric SE (SCHN)	0,000198	0,127409	0,000021	0,046518	0,870647
Airbus Group SE (AIR)	0,000250	0,113738	0,000125	0,129172	0,417413
AXA SA (AXAF)	0,000168	0,291212	0,000060	0,339981	0,462532
Air Liquide SA (AIRP)	0,000131	0,272763	0,000033	0,257119	0,603241
BNP Paribas SA (BNPP)	0,000217	0,254487	0,000119	0,247343	0,349534
Dassault Systemes SE (DAST)	0,000172	0,209065	0,000109	0,226069	0,295352
Vinci SA (SGEF)	0,000123	0,204943	0,000026	0,163219	0,673722
Pernod Ricard SA (PERP)	0,000116	0,204125	0,000075	0,183976	0,309428

Capgemini SE (CAPP)	0,000220	0,153933	0,000105	0,190019	0,427088
Safran SA (SAF)	0,000166	0,277896	0,000046	0,186979	0,599516
Danone SA (DANO)	0,000124	0,071946	0,000055	0,069260	0,509868
STMicroelectronics NV (STM)	0,000527	0,066307	0,000243	0,089851	0,488131
Compagnie de Saint Gobain SA (SGOB)	0,000187	0,172626	0,000017	0,215261	0,745994
Orange SA (ORAN)	0,000152	0,177733	0,000026	0,248074	0,645638
Engie SA (ENGIE)	0,000160	0,185386	0,000089	0,163928	0,377040
Thales (TCFP)	0,000128	0,291189	0,000057	0,239461	0,438203
Compagnie Generale des Etablissements Michelin SCA (MICP)	0,000218	0,017244	0,000171	0,045146	0,187202
Legrand SA (LEGD)	0,000128	0,198313	0,000058	0,301254	0,404711
Veolia Environnement VE SA (VIE)	0,000148	0,169882	0,000033	0,168446	0,644900
Teleperformance SE (TEPRF)	0,000163	0,287675	0,000089	0,222586	0,372312
Eurofins Scientific SE (EUFI)	0,007547	0,000000	0,007553	0,000000	0,000000
Publicis Groupe SA (PUBP)	0,000199	0,227028	0,000118	0,274877	0,308888
Carrefour SA (CARR)	0,000237	0,080772	0,000154	0,100113	0,308743
Bouygues SA (BOUY)	0,000170	0,323862	0,000058	0,318131	0,447847
Renault SA (RENA)	0,000321	0,179616	0,000051	0,214690	0,672966
DAX 30	0,000097	0,207882	0,000032	0,204200	0,539100
SAP SE (SAPG)	0,000163	0,116001	0,000111	0,117667	0,284238
Siemens AG Class N (SIEGn)	0,000162	0,170853	0,000151	0,169626	0,069194
Airbus	0,000280	0,883542	0,000691	0,198796	0,547191
Volkswagen AG VZO O,N, (VOWG_p)	0,000287	0,280289	0,000086	0,199139	0,597894
Deutsche Telekom AG Na (DTEGn)	0,000126	0,255991	0,000026	0,209347	0,646260
Merck KGaA (MRCG)	0,000164	0,124682	0,000058	0,144140	0,547198
Mercedes Benz Group AG (MBGn)	0,000231	0,078035	0,000078	0,253677	0,495127
Deutsche Post AG NA O,N, (DPWGn)	0,000161	0,139478	0,000057	0,133275	0,553553
10,-BASF SE NA O,N, (BASFn)	0,000188	0,045995	0,000056	0,094835	0,621440
Bayerische Motoren Werke AG (BMWG)	0,000200	0,166775	0,000065	0,211520	0,520485
Bayer AG NA (BAYGn)	0,000252	0,134522	0,000101	0,232071	0,428360
Infineon Technologies AG NA O,N, (IFXGn)	0,000343	0,133106	0,000121	0,172611	0,516626
Adidas AG (ADSGn)	0,000228	0,156173	0,000231	0,144181	0,000000
Vonovia SE (VNAn)	0,000158	0,173447	0,000005	0,076116	0,896860
Muench, Rueckvers, VNA O,N, (MUVGn)	0,000108	0,139147	0,000035	0,122048	0,617189
E,ON SE (EONGn)	0,000211	0,383386	0,000058	0,397831	0,524506
Henkel & Co KGaA AG Pref (HNKG_p)	0,000159	0,014707	0,000032	0,180341	0,652226
Sartorius AG VZO O,N, (SATG_p)	0,000465	0,000000	0,000423	0,647854	0,244426
Deutsche Boerse AG (DB1Gn)	0,000153	0,179491	0,000039	0,144922	0,645808
Porsche Automobil Holding SE (PSHG_p)	0,000299	0,186878	0,000052	0,290784	0,598192
Symrise AG Inh, O,N, (SY1G)	0,000146	0,165124	0,000055	0,112942	0,599664
Heidelbergcement AG O,N, Company Profile	0,000214	0,072020	0,000071	0,094113	0,577692
Zalando SE (ZALG)	0,000478	0,201032	0,000498	0,159460	0,000000
Allianz SE VNA O,N, (ALVG)	0,000121	0,237014	0,000055	0,220575	0,405399
Puma SE (PUMG)	0,000347	0,000000	0,018327	0,385989	0,364226

MTU Aero Engines NA O,N, (MTXGn)	0,000186	0,157568	0,000022	0,081057	0,804728
Brenntag AG (BNRGn)	0,000202	0,044537	0,000166	0,054899	0,234072
Qiagen NV (QIA)	0,000215	0,511326	0,000080	0,484012	0,483391
Covestro AG (1COV)	0,000357	0,000000	0,000586	0,395734	0,001024
HelloFresh SE (HFGG)	0,000389	0,483252	0,000134	0,317224	0,581532
Nikkei 225	0,000112	0,259790	0,000038	0,273432	0,486092
NEC Corp, (6701)	0,000293	0,000000	0,000474	0,540472	0,371135
Mitsubishi Heavy Industries Ltd, (7011)	0,000184	0,349755	0,000406	0,632939	0,113210
Dentsu Inc, (4324)	0,000328	0,183735	0,000162	0,173601	0,424370
Isuzu Motors Ltd, (7202)	0,000320	0,199264	0,000069	0,213876	0,656041
ANA Holdings Inc (9202)	0,000148	0,115447	0,000020	0,138172	0,751866
Daiwa Securities Group Inc, (8601)	0,000201	0,258441	0,000096	0,289365	0,348866
Toray Industries Inc, (3402)	0,000194	0,182547	0,000093	0,201280	0,414438
Minebea Mitsumi Inc (6479)	0,000521	0,193189	0,000166	0,225600	0,536258
AGC Inc (5201)	0,000273	0,241804	0,000129	0,263726	0,410387
Meiji Holdings Co, Ltd, (2269)	0,000249	0,205945	0,000041	0,188689	0,726051
CyberAgent Inc (4751)	0,000607	0,048057	0,000286	0,054449	0,501301
Ricoh Co, Ltd, (7752)	0,000308	0,080047	0,000222	0,132754	0,234106
Tokyo Electric Power Co, Inc, (9501)	0,000303	0,344929	0,000080	0,378301	0,503969
Hitachi Construction Machinery Co (6305)	0,000405	0,105266	0,000038	0,101375	0,834514
Tobu Railway Co, Ltd, (9001)	0,000130	0,376740	0,000094	0,349574	0,221134
Tosoh Corp, (4042)	0,000436	0,107550	0,000116	0,180756	0,617106
Mazda Motor Corp (7261)	0,000282	0,328085	0,000031	0,279430	0,655134
Nisshin Seifun Group Inc, (2002)	0,000200	0,226596	0,000093	0,232820	0,426653
Sumitomo Dainippon Pharma Co Ltd (4506)	0,000363	0,331536	0,000166	0,297257	0,424643
Haseko Corp (1808)	0,000309	0,254153	0,000090	0,331589	0,493692
DeNA Co Ltd (2432)	0,000398	0,333399	0,000067	0,281991	0,701293
Credit Saison Co, Ltd, (8253)	0,000259	0,249467	0,000078	0,164483	0,612839
Ube Industries Ltd, (4208)	0,002228	0,000000	0,002228	0,000000	0,000000
Takashimaya Co, Ltd, (8233)	0,000230	0,218191	0,000118	0,231944	0,378928
Maruha Nichiro Corp (1333)	0,000222	0,205329	0,000134	0,227535	0,309018
Nippon Light Metal Holdings Co, (5703)	0,067224	0,000000	0,001392	0,248717	0,003551
Chiyoda Corp, (6366)	0,000478	0,486254	0,000137	0,367813	0,513324
Oki Electric Industry Co, Ltd, (6703)	0,000292	0,147081	0,000059	0,280898	0,598218
Mitsui Engineering & Shipbuilding (7003)	0,000347	0,476710	0,000074	0,254411	0,642142
Unitika Ltd, (3103)	0,000394	0,192540	0,000156	0,175151	0,509830

Appendix 5. *Covid- 19 period* 2020-2021 Volatility coefficients

	ARCH		GARCH		
	ω	**α_1**	**ω**	**α_1**	**β_1**
Nasdaq 100	0,000175	0,418789	0,000022	0,256549	0,650751

Apple Inc (AAPL)	0,000362	0,368953	0,000070	0,284177	0,602182
MICROSOFT (MSFT)	0,000225	0,487001	0,000028	0,205470	0,722449
Alphabet Inc Class A (GOOGL)	0,000282	0,295134	0,000074	0,196503	0,633979
Amazon.com Inc (AMZN)	0,000327	0,198009	0,000123	0,194804	0,494121
Tesla Inc (TSLA)	0,001644	0,272552	0,000158	0,199177	0,735356
Meta Platforms Inc (FB)	0,000439	0,264109	0,000093	0,216413	0,637787
PepsiCo Inc (PEP)	0,000127	0,670842	0,000019	0,221679	0,652222
Costco Wholesale Corp (COST)	0,000150	0,370116	0,000022	0,266495	0,643290
T-Mobile US Inc (TMUS)	0,000230	0,584155	0,000028	0,192529	0,742310
Booking Holdings Inc (BKNG)	0,000419	0,533419	0,000067	0,300990	0,642568
MercadoLibre Inc (MELI)	0,000797	0,326392	0,000366	0,310626	0,405442
Marriott International Inc (MAR)	0,000581	0,576775	0,000090	0,191508	0,720498
Marvell Technology Group Ltd (MRVL)	0,000796	0,194283	0,000130	0,228061	0,641056
Baidu Inc (BIDU)	0,000775	0,300794	0,000286	0,322958	0,455505
KLA-Tencor Corporation (KLAC)	0,000752	0,242915	0,000135	0,214815	0,679312
Keurig Dr Pepper Inc (KDP)	0,000114	0,898072	0,000053	0,474072	0,413626
Illumina Inc (ILMN)	0,000434	0,377343	0,000078	0,227287	0,661363
NetEase Inc (NTES)	0,000174	0,620553	0,000036	0,410872	0,526309
American Electric Power Company Inc (AEP)	0,000812	0,100876	0,000359	0,138055	0,445761
Walgreens Boots Alliance Inc (WBA)	0,000324	0,571439	0,000158	0,456719	0,325093
Xcel Energy Inc (XEL)	0,000162	0,562242	0,000051	0,315908	0,503446
Ross Stores Inc (ROST)	0,000434	0,629413	0,000108	0,378552	0,491373
Dollar Tree Inc (DLTR)	0,000384	0,540039	0,000117	0,463679	0,481220
PCAR Historical Data	0,000265	0,316581	0,000079	0,245861	0,578610
Copart Inc (CPRT)	0,000235	0,655000	0,000070	0,369238	0,517369
ANSYS Inc (ANSS)	0,000402	0,320916	0,000058	0,252423	0,646031
Okta Inc (OKTA)	0,000664	0,282321	0,000198	0,237046	0,556723
Sirius XM Holding Inc (SIRI)	0,000270	0,646524	0,000066	0,378389	0,516393
Seagen Inc (SGEN)	0,000551	0,219903	0,000139	0,165521	0,627331
DocuSign Inc (DOCU)	0,000941	0,604895	0,000235	0,420340	0,491755
FTSE 100	0,000119	0,477830	0,000021	0,410414	0,481360
Samsung Electronics Co Ltd DRC (0593xq)	0,000306	0,349329	0,000063	0,207966	0,646197
Shell PLC (SHEL)	0,000438	0,572470	0,000119	0,341107	0,522847
AstraZeneca PLC (AZN)	0,000288	0,044170	0,000047	0,287041	0,599466
HSBC Holdings PLC (HSBA)	0,000425	0,069153	0,000089	0,204257	0,638044
Unilever PLC (ULVR)	0,000174	0,190932	0,000047	0,316329	0,506010
Rio Tinto PLC (RIO)	0,000396	0,236974	0,000093	0,141788	0,655988
Diageo PLC (DGE)	0,000172	0,538532	0,000025	0,293476	0,651093
GlaxoSmithKline PLC (GSK)	0,000187	0,160280	0,000016	0,164208	0,761774
BP PLC (BP)	0,000521	0,491103	0,000062	0,266427	0,679903
British American Tobacco PLC (BATS)	0,000211	0,335887	0,000077	0,256171	0,479190
Rolls-Royce Holdings PLC (RR)	0,001050	0,820447	0,000166	0,343607	0,613016
Bunzl PLC (BNZL)	0,000179	0,434285	0,000038	0,313059	0,575873

InterContinental Hotels Group PLC (IHG)	0,000575	0,330772	0,000094	0,214086	0,670573
Rentokil Initial PLC (RTO)	0,000226	0,497806	0,000075	0,335750	0,464703
Mondi PLC (MNDI)	0,000273	0,300655	0,000055	0,301546	0,586176
Admiral Group PLC (ADML)	0,000205	0,179484	0,000081	0,222162	0,431374
Schroders PLC (SDR)	0,000277	0,425412	0,000047	0,242688	0,652753
Next PLC (NXT)	0,000347	0,599959	0,000087	0,320045	0,534084
Halma PLC (HLMA)	0,000221	0,260077	0,000076	0,250178	0,488067
Spirax-Sarco Engineering PLC (SPX)	0,000225	0,236997	0,000029	0,193401	0,728111
Fresnillo PLC (FRES)	0,000689	0,235362	0,000148	0,250142	0,612874
DS Smith PLC (SMDS)	0,000427	0,126980	0,000101	0,250469	0,579336
EasyJet PLC (EZJ)	0,001634	0,202225	0,000440	0,117770	0,655538
ITV PLC (ITV)	0,000602	0,312580	0,000081	0,178483	0,705703
Hikma Pharmaceuticals PLC (HIK)	0,000294	0,206273	0,000101	0,212742	0,536599
Centrica PLC (CNA)	0,000199	0,800216	0,000179	0,746099	0,068534
Abrdn PLC (ABDN)	0,000380	0,545209	0,000029	0,172652	0,770471
Berkeley Group Holdings PLC (BKGH)	0,000292	0,436835	0,000097	0,231487	0,513052
Johnson Matthey PLC (JMAT)	0,000526	-0,009306	0,000137	0,185234	0,595127
Tui AG NA (TUIT)	0,001583	0,449968	0,000510	0,418707	0,465827
CAC 40	0,000114	0,846194	0,000014	0,315939	0,640724
Moet Hennessy Louis Vuitton SE (LVMH)	0,000301	0,190301	0,000054	0,145693	0,712617
L'Oreal SA (OREP)	0,000200	0,194445	0,000029	0,229189	0,656831
TotalEnergies SE (TTEF)	0,000341	0,693643	0,000043	0,235475	0,697868
Hermes International SCA (HRMS)	0,000221	0,220797	0,000071	0,200607	0,541528
Sanofi SA (SASY)	0,000167	0,168139	0,000029	0,233582	0,629177
Schneider Electric SE (SCHN)	0,000276	0,350450	0,000013	0,130463	0,827383
Airbus Group SE (AIR)	0,000663	0,594266	0,000097	0,281850	0,651183
AXA SA (AXAF)	0,000249	0,910908	0,000044	0,345182	0,589636
Air Liquide SA (AIRP)	0,000117	0,479742	0,000023	0,269235	0,659234
BNP Paribas SA (BNPP)	0,000468	0,424210	0,000083	0,257262	0,630437
Dassault Systemes SE (DAST)	0,000170	0,702860	0,000063	0,370809	0,501667
Vinci SA (SGEF)	0,000395	0,497768	0,000054	0,304362	0,650946
Pernod Ricard SA (PERP)	0,000166	0,247742	0,000020	0,133231	0,785226
Capgemini SE (CAPP)	0,000274	0,579574	0,000030	0,192999	0,711517
Safran SA (SAF)	0,000559	0,603558	0,000061	0,281544	0,661001
Danone SA (DANO)	0,000159	0,442645	0,000027	0,235019	0,662175
STMicroelectronics NV (STM)	0,000551	0,321302	0,000090	0,198996	0,687687
Compagnie de Saint Gobain SA (SGOB)	0,000287	0,839591	0,000561	0,326865	0,070634
Orange SA (ORAN)	0,000240	0,044682	0,000023	0,271705	0,660503
Engie SA (ENGIE)	0,000329	0,163146	0,000023	0,275455	0,690034
Thales (TCFP)	0,000265	0,700749	0,000068	0,308428	0,570893
Compagnie Generale des Etablissements Michelin SCA (MICP)	0,000281	0,407051	0,000021	0,208584	0,739999
Legrand SA (LEGD)	0,000153	0,960374	0,000026	0,297375	0,648728
Veolia Environnement VE SA (VIE)	0,000254	0,516399	0,000043	0,263202	0,655261

Teleperformance SE (TEPRF)	0,000297	0,304389	0,000020	0,213311	0,740134
Eurofins Scientific SE (EUFI)	0,000334	0,563438	0,000152	0,485993	0,362470
Publicis Groupe SA (PUBP)	0,000376	0,527211	0,000055	0,250656	0,652747
Carrefour SA (CARR)	0,000297	0,267243	0,000053	0,218944	0,648753
Bouygues SA (BOUY)	0,000282	0,682759	0,000022	0,154864	0,791022
Renault SA (RENA)	0,000966	0,358420	0,000107	0,236698	0,699716
DAX 30	0,000190	0,426548	0,000019	0,146069	0,776706
SAP SE (SAPG)	0,000403	0,000000	0,000036	0,362563	0,605938
Siemens AG Class N (SIEGn)	0,000467	0,000000	0,000047	0,138125	0,759931
Airbus	0,000679	0,565257	0,000165	0,335749	0,537581
Volkswagen AG VZO O,N, (VOWG_p)	0,000658	0,238490	0,000062	0,154623	0,765099
Deutsche Telekom AG Na (DTEGn)	0,000202	0,183881	0,000022	0,188207	0,725377
Merck KGaA (MRCG)	0,000197	0,419892	0,000024	0,175618	0,750814
Mercedes Benz Group AG (MBGn)	0,000897	0,000000	0,000037	0,139111	0,831120
Deutsche Post AG NA O,N, (DPWGn)	0,000304	0,239564	0,000039	0,176536	0,703443
10,-BASF SE NA O,N, (BASFn)	0,000354	0,281850	0,000026	0,186067	0,761068
Bayerische Motoren Werke AG (BMWG)	0,001273	0,000000	0,000300	0,017392	0,763523
Bayer AG NA (BAYGn)	0,000401	0,187901	0,000043	0,165990	0,750010
Infineon Technologies AG NA O,N, (IFXGn)	0,000584	0,284215	0,000052	0,155458	0,787110
Adidas AG (ADSGn)	0,000386	0,217381	0,000043	0,134193	0,775990
Vonovia SE (VNAn)	0,000227	0,214644	0,000038	0,257304	0,623871
Muench, Rueckvers, VNA O,N, (MUVGn)	0,000465	0,207247	0,000025	0,207576	0,764656
E,ON SE (EONGn)	0,000209	0,124365	0,000018	0,144168	0,783248
Henkel & Co KGaA AG Pref (HNKG_p)	0,000186	0,139299	0,000018	0,131700	0,784810
Sartorius AG VZO O,N, (SATG_p)	0,000572	0,081110	0,000133	0,149994	0,638912
Deutsche Boerse AG (DB1Gn)	0,000222	0,359936	0,000019	0,167839	0,744975
Porsche Automobil Holding SE (PSHG_p)	0,000549	0,411804	0,000112	0,289731	0,575668
Symrise AG Inh, O,N, (SY1G)	0,000111	0,648895	0,000040	0,264338	0,518403
Heidelbergcement AG O,N, Company Profile	0,000418	0,338329	0,000041	0,208007	0,717916
Zalando SE (ZALG)	0,000541	0,150512	0,000175	0,179918	0,573762
Allianz SE VNA O,N, (ALVG)	0,000293	0,614919	0,000037	0,383710	0,560471
Puma SE (PUMG)	0,000453	0,163196	0,000064	0,267372	0,601779
MTU Aero Engines NA O,N, (MTXGn)	0,000627	0,547202	0,000063	0,197863	0,729535
Brenntag AG (BNRGn)	0,000271	0,269462	0,000034	0,196267	0,689835
Qiagen NV (QIA)	0,000269	0,016831	0,000222	0,018839	0,166134
Covestro AG (1COV)	0,000447	0,118412	0,000135	0,187773	0,554175
HelloFresh SE (HFGG)	0,001067	0,194927	0,000225	0,123979	0,694081
Nikkei 225	0,000125	0,348876	0,000046	0,279015	0,478635
NEC Corp, (6701)	0,000381	0,227296	0,000074	0,168231	0,689901
Mitsubishi Heavy Industries Ltd, (7011)	0,000331	0,243268	0,000237	0,198367	0,322666
Dentsu Inc, (4324)	0,000478	0,401823	0,000090	0,389265	0,541147
Isuzu Motors Ltd, (7202)	0,000472	0,447119	0,000365	0,424996	0,155809
ANA Holdings Inc (9202)	0,000607	0,146667	0,000051	0,109359	0,810729

Daiwa Securities Group Inc, (8601)	0,000229	0,381804	0,000072	0,350964	0,482179
Toray Industries Inc, (3402)	0,000380	0,227943	0,000076	0,183248	0,667240
Minebea Mitsumi Inc (6479)	0,000399	0,221538	0,000131	0,174300	0,570836
AGC Inc (5201)	0,000330	0,266220	0,000096	0,247834	0,587844
Meiji Holdings Co, Ltd, (2269)	0,000139	0,199035	0,000072	0,221143	0,382664
CyberAgent Inc (4751)	0,000538	0,330891	0,000394	0,357481	0,174955
Ricoh Co, Ltd, (7752)	0,000452	0,489184	0,000160	0,407726	0,452590
Tokyo Electric Power Co, Inc, (9501)	0,000472	0,238523	0,000093	0,286699	0,586611
Hitachi Construction Machinery Co (6305)	0,000459	0,221568	0,000083	0,248177	0,621363
Tobu Railway Co, Ltd, (9001)	0,000265	0,326114	0,000060	0,296354	0,560121
Tosoh Corp, (4042)	0,000324	0,193059	0,000070	0,158591	0,673151
Mazda Motor Corp (7261)	0,000867	0,103474	0,000122	0,148143	0,733284
Nisshin Seifun Group Inc, (2002)	0,000244	0,229165	0,000034	0,227314	0,671758
Sumitomo Dainippon Pharma Co Ltd (4506)	0,000555	0,109353	0,000417	0,106894	0,224586
Haseko Corp (1808)	0,000239	0,300804	0,000044	0,120674	0,743261
DeNA Co Ltd (2432)	0,000430	0,273194	0,000275	0,287766	0,269609
Credit Saison Co, Ltd, (8253)	0,000509	0,151111	0,000217	0,138254	0,484393
Ube Industries Ltd, (4208)	0,000286	0,165715	0,000052	0,140960	0,697311
Takashimaya Co, Ltd, (8233)	0,000447	0,145777	0,000169	0,187529	0,508198
Maruha Nichiro Corp (1333)	0,000267	0,158898	0,000092	0,158912	0,555601
Nippon Light Metal Holdings Co, (5703)	0,000385	0,185054	0,000030	0,098944	0,836346
Chiyoda Corp, (6366)	0,000721	0,300216	0,000375	0,332700	0,346610
Oki Electric Industry Co, Ltd, (6703)	0,000332	0,228328	0,000124	0,200720	0,516227
Mitsui Engineering & Shipbuilding (7003)	0,000819	0,408082	0,000364	0,329365	0,420358
Unitika Ltd, (3103)	0,000511	0,391024	0,000260	0,299925	0,372975