Financial COVID-19 Crisis: an Empirical Study and Prediction of Some Stock Market Indices

Abderrahmane Moussi, Ahmed Ouazza

***Abstract*—The main purpose of this paper is to highlight the direct linear relationship between the financial markets crash and the COVID-19 pandemic daily data. Moreover, we propose efficient modeling able to predict the values of some stock market indices without statistical learning. To achieve this goal, we first carry out a statistical study of the effects of COVID-19 daily data on some European, American and Chinese stock indices during the period from December 31, 2019 until July 31, 2020 which will be divided into two phases. This study is accomplished particularly by evaluation of the correlations between these various stock market indices, between these indices and the pandemic daily data of the concerned countries as well as by the study of changes in stock market indices returns and daily volatility during the pandemic. We also establish linear regression models using stepwise method, then predictions successfully made.**

The obtained results by applications on real data show that the first period is marked by a linear causal relationship between the values of the studied stock indices, the Chinese COVID-19 data and the values of CSI300 index. While in the second period, the evolution of the studied indices is characterized by a linear causal relationship with the American COVID-19 data and the NYSE index evolution.

***Index Terms*—COVID-19, correlation, multiple linear regression, prediction, stepwise method, stock market indices, volatility.**

I. Introduction

In order to face to the COVID-19 pandemic, emergency measures undertook by authorities around world with confinement policies which differ according to the nature of the political regimes, the pandemic state and the economic situations of each country. These measures concern essentially social distancing, mandatory business closures, markets shutdown and travel restrictions. Moreover, borders between countries were closing successively and the weekly frequency of international flights fell by 75% from mid-March to early May [1]. As a result of the COVID-19 pandemic and the taken emergency measures, several economic sectors have known significant disruptions prompting the International Monetary Fund (IMF) to announce pessimistic projections about global growth. Indeed, global growth was projected at -4.9% in 2020, at -8% for advanced countries and at -3% for emerging and developing countries [2]. As for the unemployment rate in the Euro zone, it is expected to increase from 7.5% in 2019 to 9.6% in 2020 (*https://ec.europa.eu/*). This rate exceeded 20% in the USA in May 2020 (twice as high as during the recession of 2009)[3]. In China, the unemployment rate stood at 5.7% in June, against 5.9% in May and an all-time high of 6.2% in February (*https://www.cnbc.com/*).

Financial markets were also severely affected by COVID-19. In this sense, *J.W. Goodell* [4] reviewed the scant research on pandemics and finance and highlights the enormous impacts of COVID-19 on financial markets and institutions, either directly or indirectly. The author concluded that COVID-19 will shape future investigations of tail risk and financial markets. *S.R. Baker et al.* [1] worked on U.S. stock market using the text-based methods to demonstrate that no previous infectious disease outbreak, including the Spanish flu, the pandemics in 1957-1958, and 1968, has affected the stock market as forcefully as the COVID-19 pandemic. Additionally, authors underlined that in the period from February 24 to March 24, 2020, 18 market jumps in 22 trading days, more than any other period in history with the same number of trading days. *M.Mazur et al.* [3] studied the March 2020 stock market crash and they found that approximately 90% of the S&P1500 stocks generate asymmetrically distributed large negative returns and exhibit extreme volatility. Moreover, firms operating in crude petroleum, real estate, entertainment and hospitality sectors plummet considerably losing more than 70% of their market capitalizations which bring the authors of to report that March 2020 marks one of the biggest stock market crashes in history. To support these conclusions, we can quote that for the first time in history, in April 20, the price of a barrel of West Texas Intermediate (WTI), the benchmark for US oil, goes through a low of $-41 to end the day at $-37 a barrel.

Concerns about COVID-19 prompted investors to turn towards safe-havens like gold. This gold craze pushed the price of gold on August 4, 2020, above $2,000 per ounce which is a historical record. Other safe-havens which performed during COVID-19 crisis were cryptocurrencies. To highlight this, *E.Mnif et al.*[5] worked on five cryptocurrencies on a daily basis frequency. The data was then split into two periods corresponding to before and after the date of the COVID-19 outbreak. Authors found the existence of herding behavior in the five top cryptocurrency markets using the generalized Hurst exponent as an evaluation measurement of fractality by means of the multi-fractal detrended fluctuation approach. The empirical results proved that COVID-19 has a positive impact on the cryptocurrency market efficiency. In the same way, *J.W. Goodell and S.Goutte*[6] applied wavelet methods to daily data of COVID-19 world deaths and daily Bitcoin prices from 31^{th} December 2019 to 29^{th} April 2020 to investigate the co-movement of Bitcoin with levels of COVID-19 related fatalities. They found that, especially, for the period post April 5, levels of COVID-19 caused a rise in Bitcoin prices.

Manuscript received October 12, 2020; revised June 05, 2021.

Abderrahmane Moussi is a Professor of Economics Department, Mohammed first University, Oujda, Morocco (corresponding author e-mail: abderrahmane.moussi@gmail.com).

Ahmed Ouazza is a Professor of the National Institute of Statistics and Applied Economics, Rabat, Morocco (e-mail: ouazzaahmed@gmail.com).

Among statistical works which deal with correlation between stock market indices during periods of high movements such as the period related to the financial crisis resulting from COVID-19 pandemic, we can cite *A.Ang and J.Chen* [7] who assert that the observed increase in market dependence during up-markets and down-markets is not the result of a higher volatility regime. This result was supported by *S.M. Bartram and Y-H Wang* [9] when explored the impact of volatility on market dependence, more broadly, using simulated time-series of financial asset returns to show that market dependence is not generally conditional on volatility regimes. Moreover, they found that contagion indeed exists as a real phenomenon during financial crises.

At the opposite, *J.K Forbes and R.Rigobon* [10] studied cross-market correlations during periods of market crises to confirm the existence of interdependence and shown that correlation coefficients are conditional on market volatility. Furthermore, authors affirmed that aside from this conditioned interdependence there is no contagion during crisis periods. More generally, *A.Ang and G.Bekaert* [11] studied the international diversification and affirmed the existence of a high volatility-high correlation regime which is persistent between U.S.-UK and U.S.-UK-German stock markets. *G.Bekaert et al.* [12] reported a similar finding for European, Asian, and Latin American markets. More recent work going in the same direction concerning the relationship between the high volatility and markets correlation is that of *L.S. Junior and I. D.P. Franca* [13] who used the eigenvalues and eigenvectors of correlations matrices of some of the main financial market indices in the world and shown that high volatility of markets is directly linked with strong correlations between them which means that markets tend to behave as one during great crashes.

The prediction of financial movements is interesting and the issue attracted both financiers and mathematicians-statisticians. The most popular tools used for this purpose in the literature are statistical methods with and without learning. In this sense, the artificial neural network (ANN) was used by *A. H. Moghaddam et al.* [14] to forecast the daily NASDAQ stock exchange rate. In [15], E. Guresen et al. evaluated the effectiveness of neural network models to predict stock-market values. The models analyzed are multilayer perceptron, dynamic artificial neural network and the hybrid neural networks which use generalized autoregressive conditional heteroscedasticity (GARCH) to extract new input variables. *C. Liu et al.* [16] investigated four supervised learning models, including logistic regression, Gaussian discriminant analysis, naive Bayes and support vector machine (SVM) in the forecast of S&P 500 index. They concluded that a SVM model with a radial basis function kernel can achieve an accuracy rate of 62.51% for the future market trend of the studied index. Prediction of stock market trend studied also by *X. Jiawei and T.Murata* [17] using LSTM (Long Short-Term Memory) and sentiment analysis. The authors stated that their method improved accuracy than support vector regression by about 20%. More recently, *A. S. Girsang et al.* [8] used the LSTM to predict stock price and the search economics algorithm to reduce both time and computational complexity. In order to predict index returns, *Z. Ge et al.* [21] proposed a new concept of the market structure disagreement and measured it based on the K-means clustering algorithm and Gini impurity. More particular, *Ş.Sakaraya et al.* [18] studied the context of global crisis period (July 2007-December 2009) examining the predictability of daily and weekly returns of BIST-100 index by using ANN and stated that produced results are good in terms of prediction with an accuracy margin error of less than 5%.

In the present work, we study the effects of COVID-19 daily data on some principal stock market indices in Europe and USA, namely, CAC40, DAX 30, FTSE100, DJIA, NASDAQ, S&P500 and NYSE in addition to the Chinese index CSI300. The main idea is to detect eventual direct consequences of daily COVID-19 data on these indices values, whether at the level of recorded volatilities or at the level of returns. The pandemic impact on correlations of different indices is also studied.

We consider the period between December 31, 2019 and July 31, 2020. First, we carry out an overview on the important movements observed on the studied indices and their correlation with the daily data of COVID-19. Secondly, we analyze the evolution of the linear correlations between studied indices. Then, we divide the period into two phases; the first one is from December 31, 2019 to March 31, 2020 when the seven indices were influenced by the Chinese market, via the CSI300 Index, and by Chinese daily data related to COVID-19. The second phase is from April 1, 2020 to July 31, 2020 in which we particularly highlight the influence of the NYSE index values and pandemic data of USA on the European indices. For each period, we study the evolution of dependencies and also build predictive linear regression models to explain movements of the European and American indices.

II. Data and Variables

We consider closing values of eight stock market indices that are: CAC40, DAX 30, FTSE100, CSI300, DJIA, NASDAQ, S&P500 and NYSE. Data were downloaded from (*www.investing.com*). Consequently, the used pandemic data are the daily data related to COVID-19 concerning China, France, Germany, UK and USA published by the WHO, downloadable file on the link (*https://github.com/owid/covid-19-data/tree/master/public/data*). We summarize used variables and their significations:

- TC_f, NC_f, TD_f, ND_f : respectively, the total number of cumulated cases in France, the new cases daily recorded in France, the total number of deaths and the new deaths recorded each day in France.
- TC_g, NC_g, TD_g, ND_g : respectively, the total number of cumulated cases in Germany, the new cases daily recorded in Germany, the total number of deaths and the new deaths recorded each day in Germany.
- TC_{uk}, NC_{uk}, TD_{uk}, ND_{uk} : respectively, the total number of cumulated cases in United Kingdom, the new cases daily recorded in United Kingdom, the total number of deaths and the new deaths recorded each day in United Kingdom.
- TC_c, NC_c, TD_c, ND_c : respectively, the total number of cumulated cases in China, the new cases daily recorded in China, the total number of deaths and the new deaths recorded each day in China.

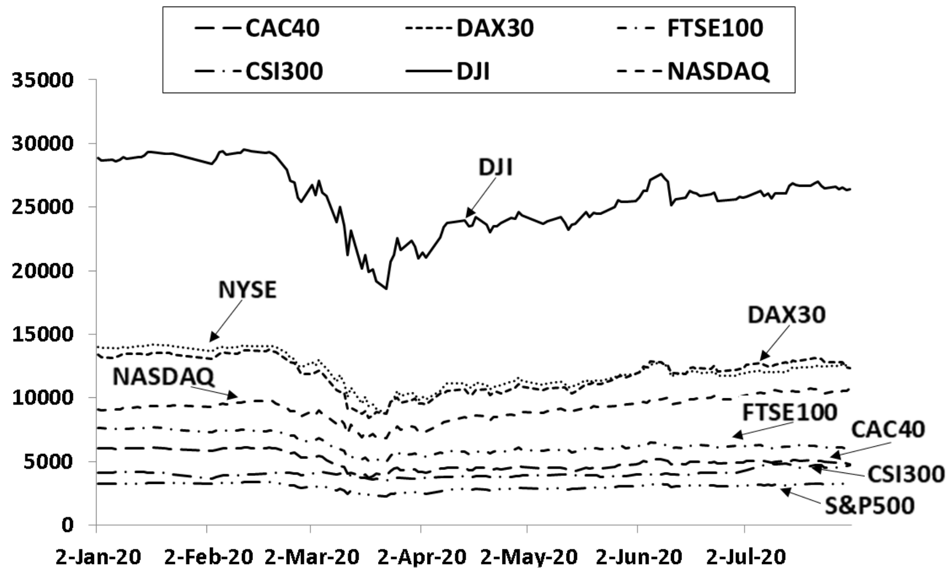


Fig. 1. Stock market movements-December 31, 2019 to July 31, 2020

- TC_{us}, NC_{us}, TD_{us}, ND_{us} : respectively, the total number of cumulated cases in United States of America, the new cases daily recorded in United States of America, the total number of deaths and the new deaths recorded each day in United States of America.

III. Stock market indices and COVID-19 : an empirical study

We focus on the period between from December 31, 2019 to July 31, 2020 to bring out the principal changing in the indices behavior through empirical indicators.
The **Fig.** 1 above gives an overview of the daily closing values of the eight indices.
It is clear that movements are significant, revealing considerable shocks with visible fall during March. Moreover, we remark that generally after the downward trend (until the end of March), the indices seem to pick up progressively with more stability. In order to explain these movements and give more account of this exceptional period, we compare the indices behavior during this pandemic period with a period without pandemic.

A. Key results on the indices movements

We present some indicators calculated from arithmetic returns of daily closing values for each index during the period from December 31,2019 to July 31,2020 with those corresponding to the same period a year earlier. The obtained results are reported in the TABLE I and TABLE II.

TABLE I
The period from December 31, 2019 to July 31, 2020

Indices	December 31, 2019 to July 31, 2020			
	Minimum of returns	Maximum of returns	Returns average	Daily volatility
$CAC40$	-12,28%	8,39%	-0,12%	2,40%
$DAX30$	-12,24%	10,98%	-0,02%	2,47%
$FTSE100$	-10,87%	9,05%	-0,14%	2,18%
$CSI300$	-7,88%	5,67%	0,11%	1,66%
$DJIA$	-12,93%	11,37%	-0,01%	2,90%
$NASDAQ$	-12,32%	9,35%	0,16%	2,67%
$NYSE$	-11,84%	10,04%	-0,04%	2,72%
$S\&P500$	-11,98%	9,38%	0,05%	2,69%

TABLE II
The period from December 31, 2018 to July 31, 2019

Indices	December 31, 2018 to July 31, 2019			
	Minimum of returns	Maximum of returns	Returns average	Daily volatility
$CAC40$	-2,03%	2,72%	0,11%	0,78%
$DAX30$	-2,67%	3,37%	0,10%	0,88%
$FTSE100$	-2,01%	2,16%	0,08%	0,67%
$CSI300$	-5,84%	5,95%	0,18%	1,48%
$DJIA$	-2,83%	3,29%	0,11%	0,76%
$NASDAQ$	-3,41%	4,26%	0,15%	0,99%
$NYSE$	-2,04%	3,06%	0,10%	0,67%
$S\&P500$	-2,48%	3,43%	0,13%	0,76%

By comparing the two periods, we notice that indices movements are all marked by positive and negative shocks widely more important during the pandemic than during the same period of the previous year. In addition, the average returns of all indices declined, with negative average returns for the CAC40, DAX30, FTSE100, DJIA and NYSE indices.
As for daily volatility, it is significantly higher during the pandemic than during the same period of the previous year with more than 2% for all indices (except for CSI300 index). Moreover, it increased by more than 200% for the CAC40, FTSE100, DJIA and S&P500 indices.
This rate of increase reaches 307% for the NYSE index and 181% for the German stock index DAX30. These increases in volatility made the US and European stock markets very risky which bring us to consider the period of COVID-19 pandemic as one of crisis that will mark the financial markets history.
Note that despite its increase, the daily volatility of the CSI300 did not behave in the same way in response to the pandemic since it recorded only an increase of 12% compared to the data of the previous year.
The high volatility was particularly visible in March 2020,

which was the month of turbulence and panic quintessential. We quote some key movements which marked this financial market crash:

- CAC40: from March 5 to March 16, it lost 34.54 % against a single increase on March 13 of just 1.83 %.
- DAX30: from March 05 to March 16, the index lost 32.13 % of its value against one increase on March 13 of only 0.77 %.
- DJIA: from February 24 to April 01, daily volatility was 5.7%.
- NASDAQ: from February 24 to March 18, daily volatility was 5.7%.
- NYSE: from March 4 to March 24, the calculated daily volatility is 6.63 %.
- S&P500: from February 28 to March 25 the daily volatility is 6.03 %.

The CSI300 rather stable, the index movements nevertheless record remarkable shocks such as the return of -7.88% recorded on February 3 and a maximum of 5.67% recorded on July 6.

B. Correlation changes across-indices

We carry out correlations comparison of the eight indices between the period from December 31, 2019 to July 31, 2020 and the same period of the previous year.
The TABLE III hereafter contains results summary.

TABLE III
Indices correlation comparison

	from December 31, 2018 to July 31, 2019							
	CAC40	DAX30	FTSE100	CSI300	DJIA	NASDAQ	NYSE	S&P500
CAC40	1	0,403	0,959	0,924	0,945	0,976	0,966	0,973
DAX30	0,403	1	0,373	0,371	0,379	0,399	0,383	0,393
FTSE100	0,959	0,373	1	0,859	0,934	0,963	0,946	0,966
CSI300	0,924	0,371	0,859	1	0,833	0,871	0,865	0,849
DJIA	0,945	0,379	0,934	0,833	1	0,964	0,990	0,975
NASDAQ	0,976	0,399	0,963	0,871	0,964	1	0,977	0,993
NYSE	0,966	0,383	0,946	0,865	0,990	0,977	1	0,985
S&P500	0,973	0,393	0,966	0,849	0,975	0,993	0,985	1
	from December 31, 2019 to July 31, 2020							
	CAC40	DAX30	FTSE100	CSI300	DJIA	NASDAQ	NYSE	S&P500
CAC40	1	0,753	0,986	0,321	0,940	0,482	0,970	0,849
DAX30	0,753	1	0,714	0,493	0,788	0,629	0,773	0,784
FTSE100	0,986	0,714	1	0,229	0,925	0,423	0,960	0,819
CSI300	0,321	0,493	0,229	1	0,466	0,783	0,413	0,603
DJIA	0,940	0,788	0,925	0,466	1	0,706	0,989	0,970
NASDAQ	0,482	0,629	0,423	0,783	0,706	1	0,615	0,853
NYSE	0,970	0,773	0,960	0,413	0,989	0,615	1	0,934
S&P500	0,849	0,784	0,819	0,603	0,970	0,853	0,934	1

While correlations between European indices were strengthened, linear correlations between American indices declined during the pandemic period compared to the period without pandemic. Otherwise, looking at the correlations between the European and American indices, we can see that values of the CAC40 index are less correlated with values of the United States indices during the pandemic while values of the DAX30 index behaved in the opposite way. As for values of the FTSE100 index, they recorded a decrease in correlation with those of the S&P500 index (very slight with the DJIA values) against a more marked fall with the NASDAQ index values. The FTSE100 index values also recorded an increase in correlation with the NYSE index compared to the same period of the previous year.
We also note considerable declines in correlation of values of the CSI300 index, whether with values of the American indices or with those of the European ones, except for DAX30 values with which an increase in correlation is noticed during the pandemic period. The changes in correlations between indices are indeed present. However, these changes have not the same magnitude and are not proportional to the changes in daily volatility discussed in the previous subsection.

C. Indices evolution and COVID-19 data

In the two previous subsections, we highlighted that the correlation across indices changed during the studied pandemic period. In addition, we showed that volatility has spectacularly increased. But is there a direct relationship between these changes and daily data from the COVID-19 pandemic?
To give an answer, we calculate the correlations between indices values and the daily COVID-19 data of the concerned countries. Intuitively, we expect that the indices values are negatively correlated with the number of COVID-19 cases, especially in home countries. This is not entirely true. Indeed, for the values of CAC40, they record a negatively stronger correlation with the daily data of the pandemic in China than with those linked to France. Values of the FTSE100 behave in the same way as those of the CAC40, with higher correlations with the Chinese pandemic data than with those of the United Kingdom. As for the values of the DAX30, they react negatively almost the same way to the COVID-19 data from Germany and China.
The correlation of CSI300 index values with the Chinese COVID-19 data is almost negligible. On the other hand, they are relatively high with the pandemic USA data (correlation of more than 0.55). For the United States indices, apart from the NASDAQ values which are positively correlated with the US pandemic daily data, the S&P500 index values do not record any significant correlation. In contrast, values of the DJIA and NYSE indices are negatively correlated with the pandemic data of China and are not so with those relating to the United States. The following TABLE IV contains the most noteworthy correlations.

TABLE IV
Correlation between indices values and some daily COVID-19 data/December 31, 2019 to July 31, 2020

	CAC40	DAX30	FTSE100	CSI300	DJIA	NASDAQ	NYSE	S&P500
TC_f	-0,42	-	-	-	-	-	-	-
TD_f	-0,42	-	-	-	-	-	-	-
NC_g	-	-0,68	-	-	-	-	-	-
ND_g	-	-0,53	-	-	-	-	-	-
TC_{uk}	-	-	-0,41	-	-	-	-	-
NC_{uk}	-	-	-0,62	-	-	-	-	-
TD_{uk}	-	-	-0,40	-	-	-	-	-
TC_c	-0,74		-0,80	-	-0,63	-0,03	-0,67	-0,48
TD_c	-0,73	-0,53	-0,80	0,15	-0,56	0,15	-0,65	-0,36
TC_{us}	-	-	-	0,71	-	0,71	-0,09	0,24
NC_{us}	-	-	-	0,62	-0,18	0,51	-0,27	0,04
TD_{us}	-	-	-	0,59	-0,03	0,69	-0,15	0,20

Results of this section are relevant. In what follows, and in order to develop this empirical study, we divide the studied period into two parts: one relating to the downward trend (until the end of March) and the other related to the second phase where stock indices values seem to pick up progressively (from April 1 until July 31, 2020).

This lead us to make more precise conclusions about the effect of pandemic data on the evolution of indices.

We call entire period the period from December 31, 2019 to July 31, 2020. The first period is the period from December 31, 2019 to March 31, 2020 and the second period means the period from April 1, 2020 to July 31, 2020.

IV. The first period: statistical characteristics

To characterize the first period, we calculate some indicators. The TABLE V below contains some key results.

TABLE V
Comparison between the entire and the first period

Indices values	Periods	Minimum of returns	Maximum of returns	Returns average	Daily volatility
CAC40	Entire Period	-12,28%	8,39%	-0,12%	2,40%
	First Period	-12,28%	8,39%	-0,43%	2,91%
DAX30	Entire Period	-12,24%	10,98%	-0,02%	2,47%
	First Period	-12,24%	10,98%	-0,41%	2,90%
FTSE100	Entire Period	-10,87%	9,05%	-0,14%	2,18%
	First Period	-10,87%	9,05%	-0,41%	2,65%
CSI300	Entire Period	-7,88%	5,67%	0,11%	1,66%
	First Period	-7,88%	3,29%	-0,15%	1,94%
DJIA	Entire Period	-12,93%	11,37%	-0,01%	2,90%
	First Period	-12,93%	11,37%	-0,34%	3,82%
NASDAQ	Entire Period	-12,32%	9,35%	0,16%	2,67%
	First Period	-12,32%	9,35%	-0,18%	3,50%
NYSE	Entire Period	-11,84%	10,04%	-0,04%	2,72%
	First Period	-11,84%	10,04%	-0,41%	3,52%
S&P500	Entire Period	-11,98%	9,38%	0,05%	2,69%
	First Period	-11,98%	9,38%	-0,29%	3,56%

During the first period, we observe daily volatility greater than that relating to the entire one. This is more obvious on US stock values. Additionally, almost all maximum and minimum shocks recorded in the TABLE I are affiliated to this first period. Also, all indices register negative average returns and smaller than those of the entire period.

This leads us to revisit the correlations between indices as well as the correlations between indices and pandemic data. The following TABLE VI contains correlations achieved in the first period.

TABLE VI
Indices correlations-first period

	CAC40	DAX30	FTSE100	CSI300	DJIA	NASDAQ	NYSE	S&P500
CAC40	1	0,998	0,996	0,721	0,984	0,972	0,988	0,981
DAX30	0,998	1	0,992	0,714	0,985	0,978	0,987	0,984
FTSE100	0,996	0,992	1	0,724	0,983	0,960	0,988	0,978
CSI300	0,721	0,714	0,724	1	0,738	0,683	0,754	0,725
DJIA	0,984	0,985	0,983	0,738	1	0,986	0,998	0,998
NASDAQ	0,972	0,978	0,960	0,683	0,986	1	0,981	0,993
NYSE	0,988	0,987	0,988	0,754	0,998	0,981	1	0,996
S&P500	0,981	0,984	0,978	0,725	0,998	0,993	0,996	1

Comparing this correlations table with the TABLE III, we notice a clear increase in the Pearson coefficients calculated between the CSI300 and all other indices, except with NASDAQ which registers a slight decrease. This result is consistent with the findings of *J.K.Forbes and R.Rigobon* [10], *A. Ang and G. Bekaert* [11] , *G. Bekaert et al.* [12] and *L.S. Junior and I.D.P Franca* [13] who opt for the idea that during periods of high volatility, markets are highly correlated.
These increases in linear correlations of the European and American indices values with the CSI300 values is supported by important correlations between these values with the Chinese COVID-19 data as well as the pandemic data of the home countries of each index. These dependencies are illustrated in the TABLE VII below.

TABLE VII
Correlation between indices values and COVID-19 data-first period

CAC40	TC_f	NC_f	TD_f	ND_f
	-0,62	-0,70	-0,49	-0,56
	TC_c	NC_c	TD_c	ND_c
	-0,68	0,29	-0,81	0,33
DAX30	TC_g	NC_g	TD_g	ND_g
	-0,58	-0,67	-0,43	-0,46
	TC_c	NC_c	TD_c	ND_c
	-0,66	0,32	-0,79	0,37
FTSE100	TC_{uk}	NC_{uk}	TD_{uk}	ND_{uk}
	-0,57	-0,64	-0,44	-0,48
	TC_c	NC_c	TD_c	ND_c
	-0,74	0,27	-0,85	0,27
DJIA	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	-0,49	-0,59	-0,45	-0,47
	TC_c	NC_c	TD_c	ND_c
	-0,687	0,32	-0,80	0,34
NASDAQ	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	-0,46	-0,55	-0,42	-0,44
	TC_c	NC_c	TD_c	ND_c
	-0,58	0,38	-0,72	0,45
NYSE	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	-0,51	-0,60	-0,47	-0,49
	TC_c	NC_c	TD_c	ND_c
	-0,69	0,29	-0,81	0,33
S&P500	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	-0,49	-0,59	-0,45	-0,47
	TC_c	NC_c	TD_c	ND_c
	-0,65	0,33	-0,78	0,38

V. The second period: relative markets stabilization

The second period corresponding to April 1, 2020 to July 31, 2020 although eventful remains more stable than the first period containing the drastic shocks of March. To show this, we carry out a comparison in the TABLE VIII below.

TABLE VIII
Performance of indices between the first and the second period

Indices values	Periods	Minimum of returns	Maximum of returns	Returns average	Daily volatility
CAC40	Second Period	-4,71%	5,16%	0,12%	1,92%
	First Period	-12,28%	8,39%	-0,43%	2,91%
DAX30	Second Period	-4,47%	5,77%	0,28%	2,06%
	First Period	-12,24%	10,98%	-0,41%	2,90%
FTSE100	Second Period	-3,99%	4,29%	0,06%	1,72%
	First Period	-10,87%	9,05%	-0,41%	2,65%
CSI300	Second Period	-4,81%	5,67%	0,31%	1,41%
	First Period	-7,88%	3,29%	-0,15%	1,94%
DJIA	Second Period	-6,90%	7,73%	0,24%	1,94%
	First Period	-12,93%	11,37%	-0,34%	3,82%
NASDAQ	Second Period	-5,27%	7,33%	0,41%	1,81%
	First Period	-12,32%	9,35%	-0,18%	3,50%
NYSE	Second Period	-6,35%	6,42%	0,24%	1,91%
	First Period	-11,84%	10,04%	-0,41%	3,52%
S&P500	Second Period	-5,89%	7,03%	0,29%	1,77%
	First Period	-11,98%	9,38%	-0,29%	3,56%

We remark that the second period is much less volatile than the first one. This was visible from the **Fig.** 1. In fact, there are smaller shocks and positive return averages after they were negative during the first phase. This is a sign that the market has gradually regained stability and the market participants gradually got rid of the uncertainty.
These positive changes in the indices values can be explained by the intervention of the authorities to support their economies, in particular in the United States and

Europe, which reassured the investors by considerable measures in early April, 2020. Indeed, the Federal Reserve (FED) injected $ 2.3 trillion (versus the 750 billion dollars during the global financial crisis) and the FED's monetary committee has also kept key rates within a range of 0 to 0.25% [19]. In March, 2020, the European commission has adopted an investment initiative of 37 billion Euros in response to the COVID-19 crisis to provide liquidity to small businesses and the healthcare sector. The commission proposed further to set up a solidarity instrument called SURE. With 100 billion Euros, it aims to help workers maintain their income and support companies in difficulty [20].

Since the indices behavior changed in the second period, we revisit the correlations across-indices and compare them with those achieved during the first period of our study. The TABLE IX below contains the performed correlations from April 1 to July 31, 2020.

TABLE IX
Indices correlations-second period

	CAC40	DAX30	FTSE100	CSI300	DJIA	NASDAQ	NYSE	S&P500
CAC40	1	0,589	0,907	0,703	0,944	0,881	0,932	0,915
DAX30	0,589	1	0,500	0,522	0,570	0,580	0,561	0,574
FTSE100	0,907	0,500	1	0,497	0,914	0,816	0,893	0,874
CSI300	0,703	0,522	0,497	1	0,683	0,850	0,692	0,769
DJIA	0,944	0,570	0,914	0,683	1	0,930	0,991	0,983
NASDAQ	0,881	0,580	0,816	0,850	0,930	1	0,922	0,975
NYSE	0,932	0,561	0,893	0,692	0,991	0,922	1	0,982
S&P500	0,915	0,574	0,874	0,769	0,983	0,975	0,982	1

Compared with the TABLE VI, we remark that correlation between indices values of US did not change much, just an insignificant decline. No important changes either for the values of US indices with the values of Chinese stock index apart the NASDAQ values which are more correlated with the CSI300 values.
On the other hand, these US indices values saw their correlations with European indices values reduced, in particular with the values of the German index DAX30 and the NYSE which fell considerably. As for the correlations across values of European indices were decreases in the second period. In the same way, linear correlations between the CSI300 stock market index and European indices decreased too.
In short, correlations have generally declined by different ways apart from the correlation between the CSI300 index values and those of the NASDAQ index which increased by 24%.

It should be noted that this second period was marked by a considerable rise whether in number of daily deaths or the number of new cases daily declared relating to the pandemic in the United States and Europe, against a rather stable pandemic state in China with the exception of April 17 where there were 1290 new deaths and 352 new COVID-19 cases.

In the following TABLE X, we revisit correlations of different indices (Europeans and Americans) with COVID-19 daily data from the United States and home countries.

TABLE X
Correlation between indices values and COVID-19 data-second period

CAC40	TC_f	NC_f	TD_f	ND_f
	0,79	-0,49	0,71	-0,66
	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,78	0,52	0,84	-0,55
DAX30	TC_g	NC_g	TD_g	ND_g
	0,86	-0,71	0,83	-0,79
	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,88	0,59	0,92	-0,57
FTSE100	TC_{uk}	NC_{uk}	TD_{uk}	ND_{uk}
	0,86	-0,82	0,86	-0,71
	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,65	0,25	0,82	-0,56
NASDAQ	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,93	0,64	0,97	-0,50
DJIA	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,82	0,48	0,89	-0,49
NYSE	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,84	0,50	0,89	-0,48
S&P500	TC_{us}	NC_{us}	TD_{us}	ND_{us}
	0,89	0,57	0,94	-0,48

VI. Modeling and Prediction

In order to evaluate if the founded linear correlations are subjects to possible causal relationships or arbitrary recorded, we carry out modeling using linear regression models trying to explain the evolution of the European and American indices by the CSI300 values and Chinese pandemic data as well as those of the home countries during the first period.
In the second one, we try to explain movements of the European indices by one of the US indices and the US COVID-19 daily data as well as with COVID-19 daily data of home countries.
The statistical results of the previous sections justify the studied period division into two parts as well as this choice of explanatory variables.

A. Methodology

For the two periods, we establish classical multiple linear regression (MLR) models which are expressed by:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_k x_k + \epsilon \ , \tag{1}$$

where y is the variable to explain, $x_1, \cdots, x_k$ are explicative variables, ϵ is the model error and $a_0, \cdots, a_k$ are the regression coefficients.

Before establishing models and to avoid collinearities between different explanatory variables, we use the Variance Inflation Factor (VIF) defined by:

$$VIF_j = \frac{1}{1 - R_j^2}, \ j = 1, \cdots, k \ ;$$

where R_j^2 is the determination coefficient for regressing the j^{th} independent variable on the k-1 remaining ones. For each explanatory variable, we measured the value of the VIF, then eliminated those with $VIF > 4$.

To build our models, we proceed by the stepwise method to select the most statistically significant model through the Fisher test (F-test) with high determination coefficient value (R-squared). Moreover, the method allows to choose suitable explanatory variables.

TABLE XI
Models summary-first period

Index	Model	R^2	Adjusted R^2	Global significance: p-value (F-test)
CAC40	2,395 V_{cs}-0,009 TC_c+0,127 NC_c-3766,624	0,796	0,785	5,247$\times 10^{-19}$
DAX30	5,406 V_{cs}-0,019 TC_c+0,3 NC_c-8700,574	0,782	0,769	7,68$\times 10^{-18}$
FTSE100	2,577 V_{cs}-0,012 TC_c+0,13 NC_c-2945,905	0,831	0,822	3,2$\times 10^{-21}$
DJIA	10,516 V_{cs}-0,038 TC_c+0,554 NC_c-14000,36	0,818	0,807	6,51$\times 10^{-10}$
NASDAQ	2,794 V_{cs}-0,007 TC_c+1,171 NC_c-1982,878	0,726	0,711	6,21$\times 10^{-15}$
NYSE	5,472 V_{cs}-0,02 TC_c+0,267 NC_c-8340,018	0,832	0,822	1,71$\times 10^{-20}$
S&P500	1,096 V_{cs}-0,004 TC_c+0,06NC_c-1194,108	0,790	0,778	5.58$\times 10^{-18}$

In order to evaluate the made predictions in what follows, we use two criterions.
We recall that the prediction error rate is computed by the following formula:

$$\frac{\sum_{i=1}^{n} \frac{\mid \hat{y}_i - y_i \mid}{y_i}}{n} \times 100\ , \tag{2}$$

where n is the number of predicted values and y_i are the observations of explained variable.
Furthermore, the criterion Normalized Mean Square Error (NMSE) is defined as follows:

$$NMSE = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} y_i^2}\ , \tag{3}$$

where y_i and $\hat{y}_i$ are, respectively, the realized and predicted stock indices values.

B. The first period: CSI300 and Chinese COVID-19 data effects

1) Models building: In addition to the CSI300 index values (V_{cs}), the candidate explanatory variables for each index are Chinese COVID-19 data. Namely, the total number of cases (TC_c), new cases (NC_c), the total number of deaths recorded since the beginning of the pandemic (TD_c) and finally the number of deaths recorded each day (ND_c). The obtained models by stepwise process are summarized in the TABLE XI above.

All established models are statistically significant (F-test) and the regressions coefficients presented in the TABLE XI are significant at the level $\alpha = 5\%$ (t-test). Moreover, we observe that models are exhaustive since the R-squared and adjusted R-squared are reasonably high (greater than 0,7).

To assess the explanatory performance of Chinese pandemic data against those of home countries, we build models with explanatory variables which are the CSI300 index values, TC and NC which were the explanatory variables in the models of TABLE XI, but this time we use those relating to the home countries (total cases and new cases for each country).
The TABLE XII hereafter shows the main results.

TABLE XII
Performance indicators of models (COVID19-home countries)-first period

Indices	R-squared	Adjusted R-squared
CAC40	0,607	0,586
DAX30	0,569	0,545
FTSE100	0,589	0,567
DJIA	0,593	0,570
NASDAQ	0,513	0,485
NYSE	0,617	0,596
S&P500	0,581	0,557

Whereas the number of explanatory variables remains the same, results show a clear decrease in R-squared values, which affects the models adjustment.
This means that the evolution of Europeans and Americans stock indices in the first period are better explained by the Chinese COVID-19 daily data rather than those related to home countries. Moreover, regressions coefficients are not all significant at the level $\alpha = 5\%$ (t-test).
Consequently, we adopt the results on the TABLE XI to carry out their validations and make predictions.

2) Validation and predictions: The assumptions of residuals normality as well as the assumption of homoscedasticity are graphically verified by the models of the TABLE XI. The figures (**Fig.** 5 until **Fig.** 11) contain the Q-Q plot graphics and the residuals plot with the residual values on the ordinate and the predicted values on the abscissa.
For Q-Q plot, the points cloud are properly aligned. Concerning the residual graphics, points are distributed randomly around zero.

The TABLE XIII thereafter summarizes main indicators for the predictions quality concerning each model. We can see that all residual means have a negligible values close to zero. In addition, for each index, we record a high linear correlation between the realized values and the predicted values using the established regression models. Moreover, prediction error rates are too small with NMSE close to 0%.

To illustrate the predictions quality, the graphs (**Fig.** 2 and **Fig.** 3) thereafter represent the daily values realized by each index compared with those predicted by the established models.

TABLE XIII
Predictions characteristics-first period

Indices	Prediction error rate	NMSE	Number of prediction days	Correlation between realized and predicted values	Residual means
CAC40	4%	0,17%	18	0,87	$-5,27 \times 10^{-12}$
DAX30	1,4%	0,03%	15	0,92	$-1,12 \times 10^{-11}$
FTSE100	2,5%	0,08%	17	0,86	$-4,16 \times 10^{-12}$
DJIA	3%	0,11%	19	0,88	$-7,33 \times 10^{-12}$
NASDAQ	6%	0,4%	20	0,89	$-5,04 \times 10^{-12}$
NYSE	2%	0,06%	15	0,85	$-1,17 \times 10^{-11}$
S&P500	5%	0,26%	24	0,83	$-7,73 \times 10^{-13}$

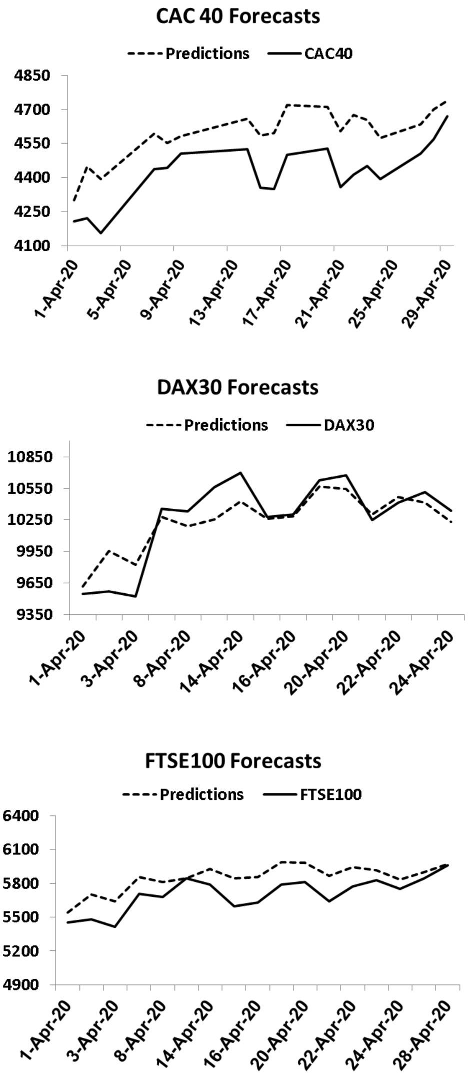


Fig. 2. Realized values and predictions made with the models of the Table XI-first period/European indices.

The statistical modeling results, especially the adjustment and prediction quality, show that for this first period, movements of the studied stock indices were particularly linked to the CSI300 index values and to the Chinese COVID-19 data. Thus, between December 31, 2019 and March 31, 2020, the Chinese financial market was a benchmark for investors in the European and American markets. In addition, the pandemic evolution in China was a key informational source for decisions in these markets.

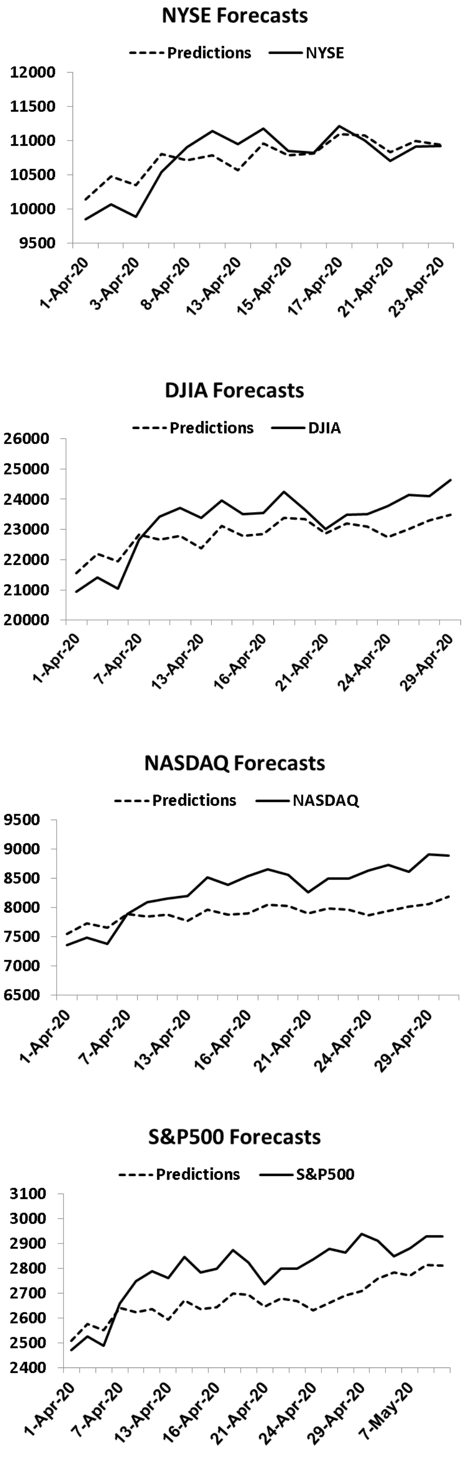


Fig. 3. Realized values and predictions made with the models of the Table XI-first period/American indices.

TABLE XIV
Models summary for the European indices-second period

Index	**Model**	R^2	**Adjusted** R^2	**Global significance: p-value (F-test)**
CAC40	0,361 V_{NY}-0,057 ND_{us}+595,643	0,884	0,881	$4,1 \times 10^{-38}$
DAX30	**Model1:** 1,343 V_{NY}-0,198 ND_{us}-3774,993	0,939	0,937	$1,28 \times 10^{-48}$
	Model2: 1,224 V_{NY}-2,472 ND_g-2451,4	0,942	0,941	$1,33 \times 10^{-48}$
FTSE100	0,288 V_{NY}-0,051 ND_{us}+2732,616	0,826	0,821	$4,66 \times 10^{-31}$

TABLE XV
Predictions characteristics-second period

		Prediction error rate	NMSE	Number of prediction days	Correlation between realized and predicted values	Residual means
CAC40		4,4%	0,21%	16	0,67	-2,05 $\times 10^{-12}$
DAX30	Model1	3,4%	0,12%	16	0,79	5,76$\times 10^{-13}$
	Model2	3,2%	0,1%	16	0,84	-4,88$\times 10^{-13}$
FTSE100		4,3%	0,19%	9	0,71	-7,88$\times 10^{-13}$

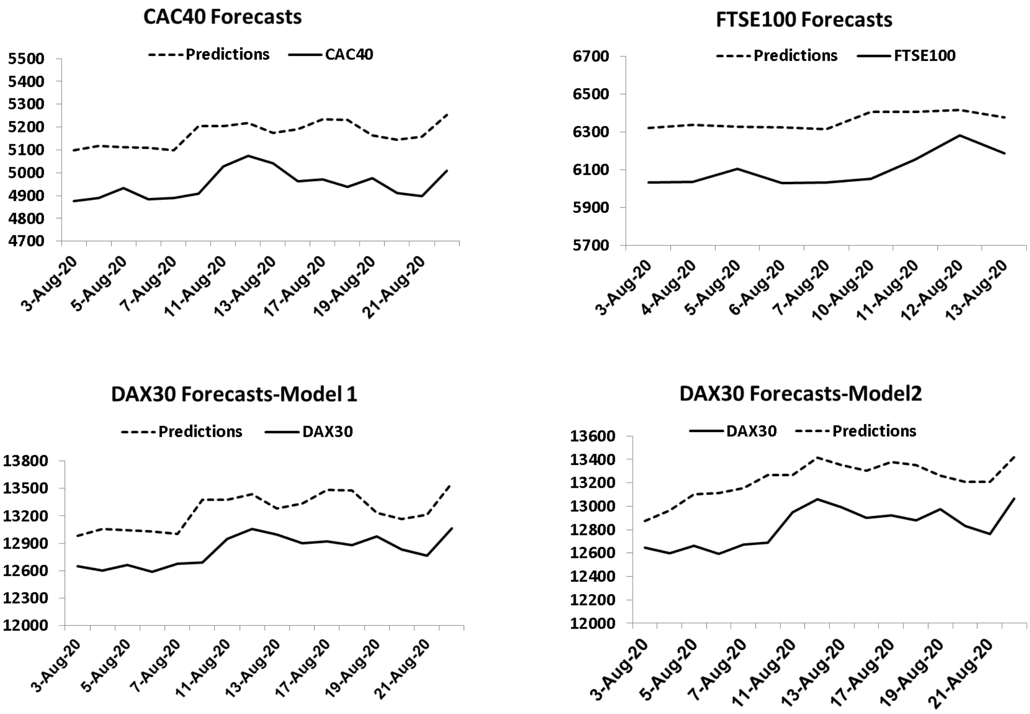


Fig. 4. Realized values of the European indices and predictions made with the models of the TABLE XIV.

C. The second period: effects of NYSE and US's COVID-19 data on the European indices

1) Models building: In order to explain the evolution of European stock indices values, the candidate explanatory variables are the American indices values as well as the daily COVID-19 data related the United States and those of home countries.

For each index, after using the stepwise process, we found that all indices values evolution is better explained by the evolution of the NYSE index values (V_{NY}) and the number of deaths daily declared in USA (ND_{us}). An exceptional case is the movement of the DAX30 index which can be explained by the evolution of the NYSE index and, either by the daily deaths in the USA (ND_{us}), or by the number of daily deaths declared in Germany (ND_g). The established linear models are summarized in the TABLE XIV above.

We notice that model2 for the DAX30 index has a slight advantage compared to model1 due to its slightly higher R-squared. On the other hand, all established models are statistically significant (F-test) and all the regressions coefficients presented in the TABLE XIV above are significant at the level $\alpha = 5\%$ (t-test). Moreover, we observe that models are exhaustive since the R-squared and adjusted R-squared are reasonably high. Therefore, we proceed to validation to make predictions.

2) Validation and predictions: To validate the models above, we proceed in the same way as the section VI-B2. The assumption of residuals normality as well as the assumption of homoscedasticity are graphically verified by the models of the TABLE XIV (see **Fig.** 12 until **Fig.** 15). In addition, all residual means have a negligible values close to zero (see the TABLE XV) and prediction error rates as well as NMSE are insignificant.

The second model for the DAX30 index is better than the first one. Indeed, as mentioned above, R-squared is higher for the second which is confirmed in terms of prediction error rate, NMSE and correlations between the realized values and the predicted values in the TABLE XV above. This proves that the evolution of the DAX30 index is better explained by the daily German COVID-19 data than those of the USA.

Predictions are made for each model and the **Fig.** 4 above shows the obtained results. These graphs represent the daily values achieved by each index compared with those predicted by the established models.

The linear modeling results show that from April 1, 2020 until July 31, 2020 a particular interest of European investors in American COVID-19 data making them a source of information influencing the evolution of indices values. This is explained especially by the stability of the pandemic state in China. Moreover, the three studied European indices were particularly linked to the American NYSE index.

VII. Conclusion

The financial crisis induced by the COVID-19 pandemic is unprecedented and their short term consequences were remarkable. Unlike the global crisis (2007-2009) which was originally a financial crisis influenced economies around the world, the crisis caused by the pandemic was originally a health and then an economic crisis affected the financial markets to be part of the financial crises history which will change necessarily the view of specialists on risk.

In the present paper, we studied the evolution of some European and American indices during the period from December 31, 2019 until July 31, 2020 related to the COVID-19 pandemic. This study concerned the correlations between these indices, their volatilities and the characteristics of their returns. After a statistical study over the entire period comparing it with the same period of the previous year, we divided it into two phases:

- First period between December 31, 2019 and March 31, 2020: characterized by a high daily volatility of indices with up and down drastic shocks. The correlations across studied indices values were high too. This period was also marked by a fall in their movements in March except the CSI300 index which seems more stable compared with the others.

  In this period, we showed that the European and American indices are linearly affected by Chinese daily COVID-19 data. This linear direct links led us to explain the European and American stock indices evolutions by building statistically valid multiple linear regression models using the stepwise method based on the explanatory variables that were CSI300 index values, the total number of cases COVID-19 and the new cases recorded daily in China. Then predictions were successfully carried out.
- Second period between April 1, 2020 and July 31, 2020: period of gradual but cautious resumption marked by a decline in terms of indices daily volatilities and shocks with particular behaves for CSI300 and NASDAQ indices which seem pick up faster than the others. Moreover, correlations across-indices fell compared with the first period but hold remarkable.

  Direct linear links were important between the values of European stock market indices and COVID-19 daily data related to the USA as well as those of home countries.

  In this period, for the purpose to explain the evolutions of the three European indices values, we built multiple linear regression models statistically valid using the stepwise method based on the explanatory variables that are the NYSE index values and the number of new deaths due to COVID-19 pandemic daily recorded in USA. We noticed that for the evolution of the DAX30 index is better explained by NYSE index values and the number of new deaths due to COVID-19 pandemic recorded daily in Germany. We finally made predictions successfully.

The direct linear causal relationship of pandemic information, daily communicated, with the evolution of some American and European stock market indices has been highlighted. Moreover, the eyes of financial market participants seem turned more to the countries suffering from the pandemic than to the financially suffering countries for the studied periods.

Despite that the adopted modeling approach is simple; the obtained results in particular in terms of predictions accuracy and recorded errors are relevant. This is all the more interesting as it gives an idea to financial analysts, traders and generally to market players, on strategies to adopt and methods to use in such pandemic context especially that the COVID-19 financial crisis has not yet over and we expect appearing of middle and long-term repercussions on stock markets.

In the future research we will try to extend our study for a larger period including more variables using other approach based on some statistical learning algorithms.

References

[1] S.R. Baker, N. Bloom, S.J. Davis, K. Kost, M. Sammon, and T. Viratyosin, "The unprecedented stock market impact of covid-19," *National Bureau of Economic Research*, no. w26945, 2020.

[2] International Monetary Fund, WORLD ECONOMIC OUTLOOK REPORTS, World Economic Outlook Update, 2020.

[3] M. Mazur, M. Dang, and M. Vega, "Covid-19 and the march 2020 stock market crash. evidence from s&p1500," *Finance Research Letters*, 2020.

[4] J.W. Goodel, "Covid-19 and finance: Agendas for future research," *Finance Research Letters*, vol. 35, no. 101512, 2020.

[5] E. Mnif, A. Jarbouib, and K. Mouakhar, "How the cryptocurrency market has performed during covid 19? a multifractal analysis," *Finance Research Letters*, vol. 36, no. 101647, 2020.

[6] J.W. Goodel and S. Goutte, "Co-movement of covid-19 and bitcoin: Evidence from wavelet coherence analysis," *Finance Research Letters*, vol. 38, pp. 101625, 2020.

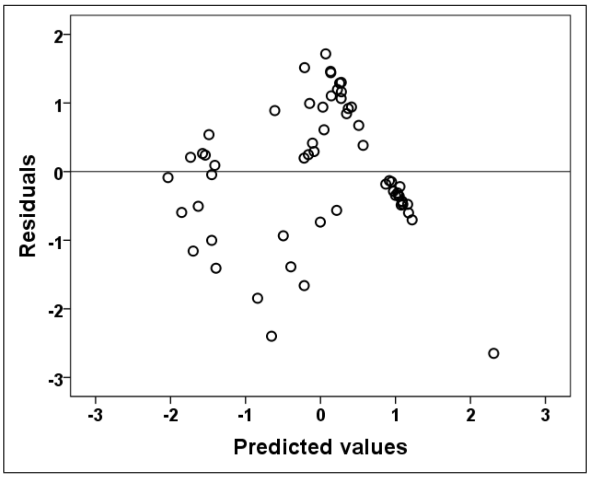
[7] A. Ang and J. Chen, "Asymmetric correlations of equity portfolios,"*Journal of Financial Economics*, vol. 63, pp. 443–494, 2002.

[8] A. S. Girsang, F. Lioexander, and D. Tanjung, "Stock Price Prediction Using LSTM and Search Economics Optimization," *IAENG International Journal of Computer Science*, vol. 47, no. 4, pp. 758–764, 2020.

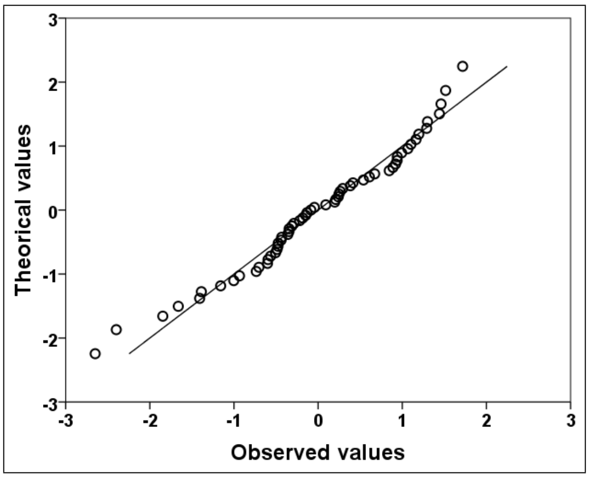
[9] S.M. Bartram and Y.-H. Wang, "Another look at the relationship between cross-market correlation and volatility," *Finance Research Letters*, vol. 2, no. 2, pp. 75–88, 2005.

[10] J.K. Forbes and R. Rigobon, "No contagion, only interdependence: Measuring stock market comovements," *The Journal Of Finance*, vol. 57, no. 5, pp. 2223–2261, 2002.

[11] A. Ang and G. Bekaert, "International asset allocation with regime shifts," *The Review of Financial Studies*, vol. 15, no. 4, pp. 11371187, 2002.

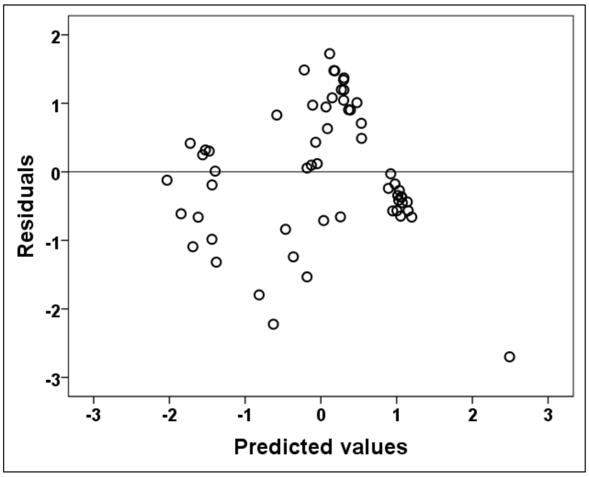


(a) Residuals plot-CAC40

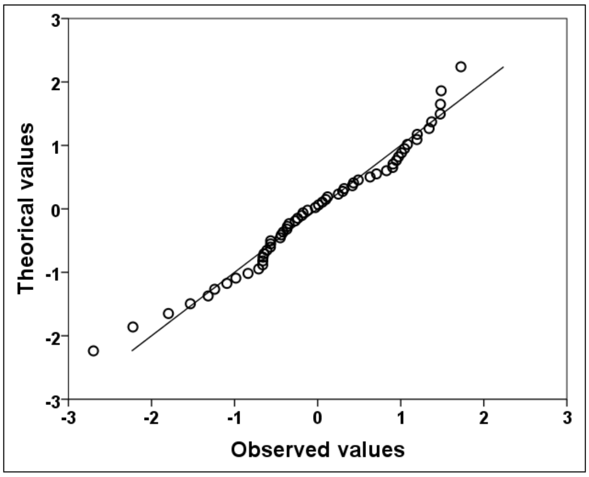


(b) Q-Q plot-CAC40

Fig. 5. Residuals normality and homoscedasticity for the CAC40 index (First period)

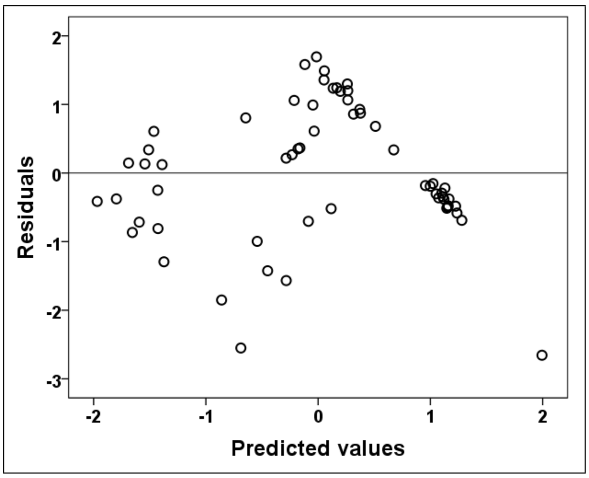


(a) Residuals plot-DAX30

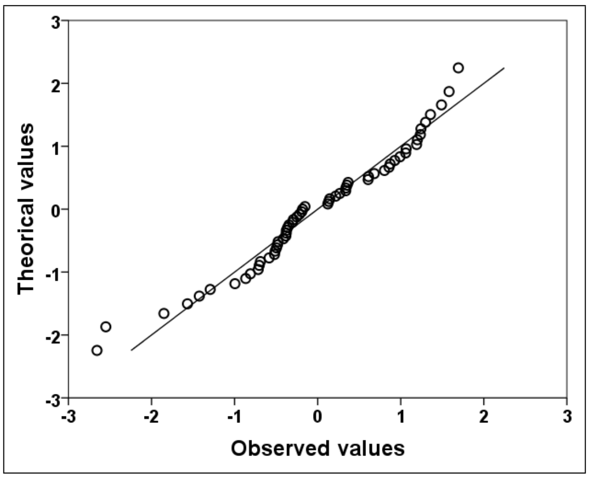


(b) Q-Q plot-DAX30

Fig. 6. Residuals normality and homoscedasticity for the DAX30 index (First period)

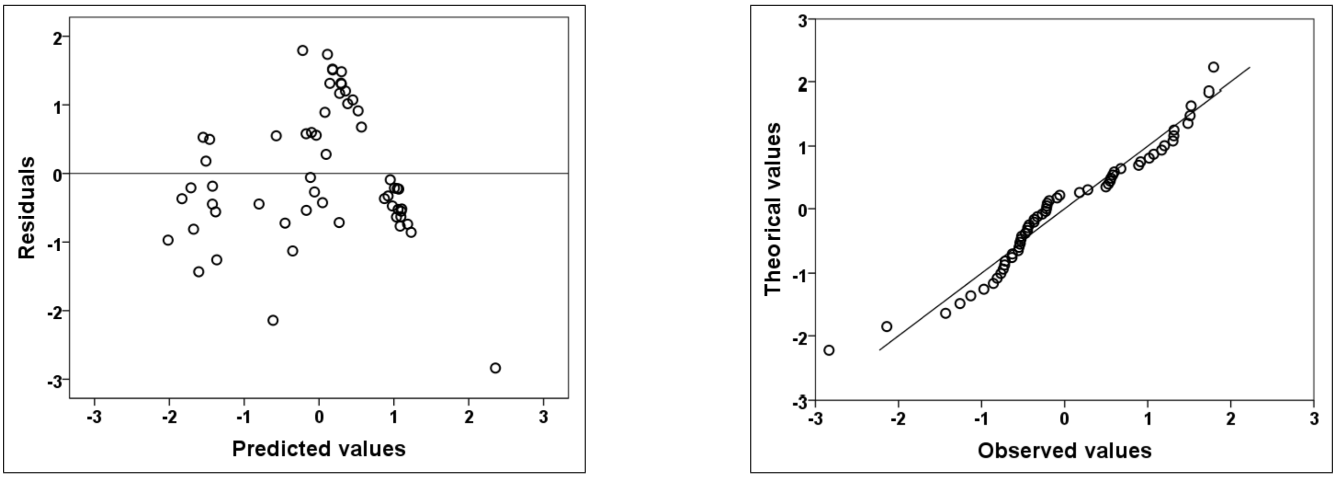


(a) Residuals plot-FTSE100



(b) Q-Q plot-FTSE100

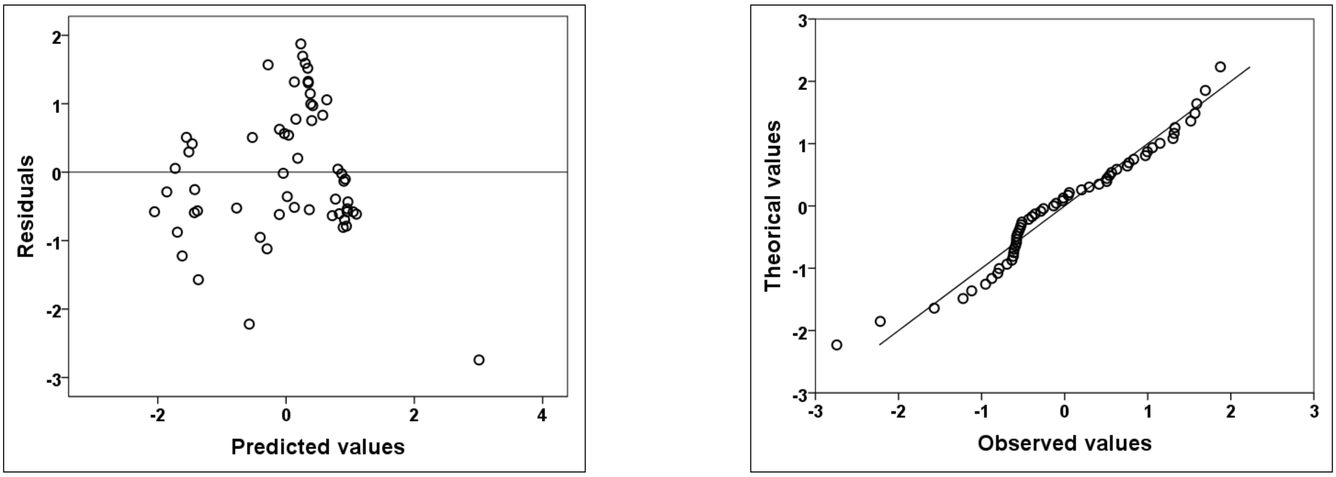
Fig. 7. Residuals normality and homoscedasticity for the FTSE100 index (First period)



(a) Residuals plot-DJIA

(b) Q-Q plot-DJIA

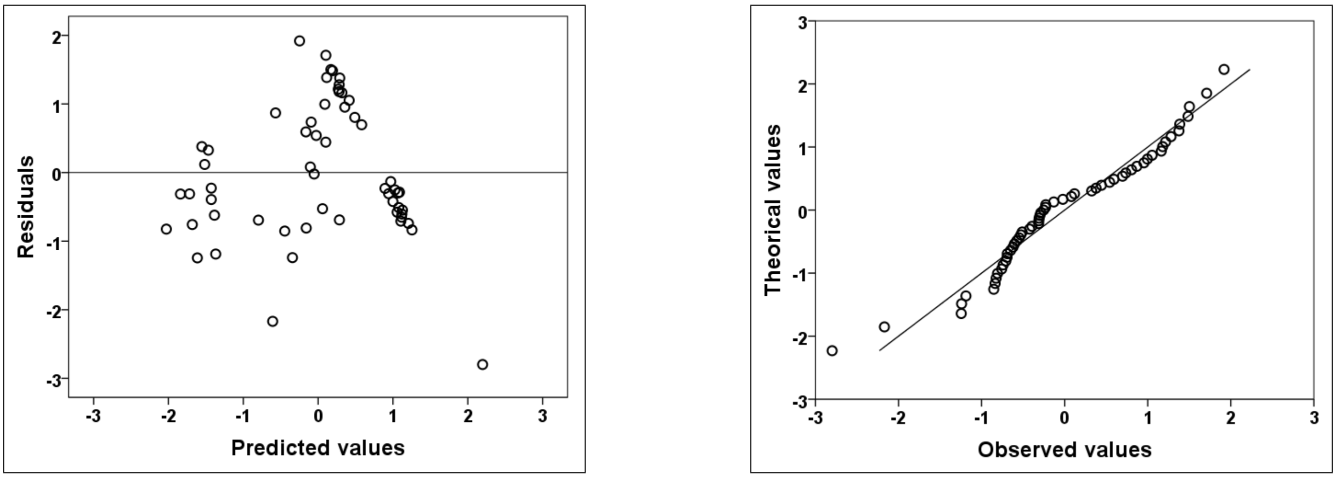
Fig. 8. Residuals normality and homoscedasticity for the DJIA index (First period)



(a) Residuals plot-NASDAQ

(b) Q-Q plot-NASDAQ

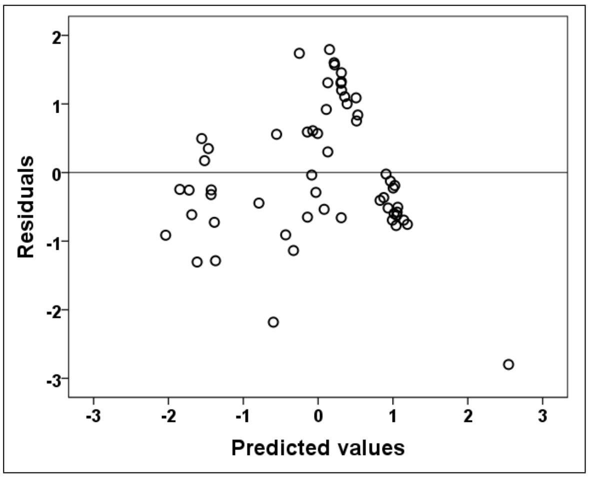
Fig. 9. Residuals normality and homoscedasticity for the NASDAQ index (First period)



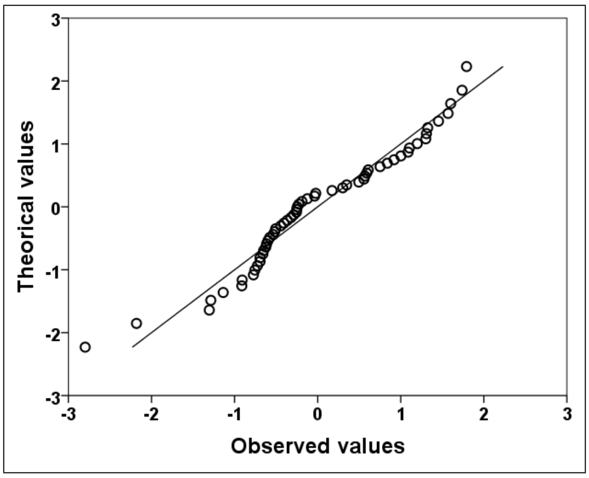
(a) Residuals plot-NYSE

(b) Q-Q plot-NYSE

Fig. 10. Residuals normality and homoscedasticity for the NYSE index (First period)

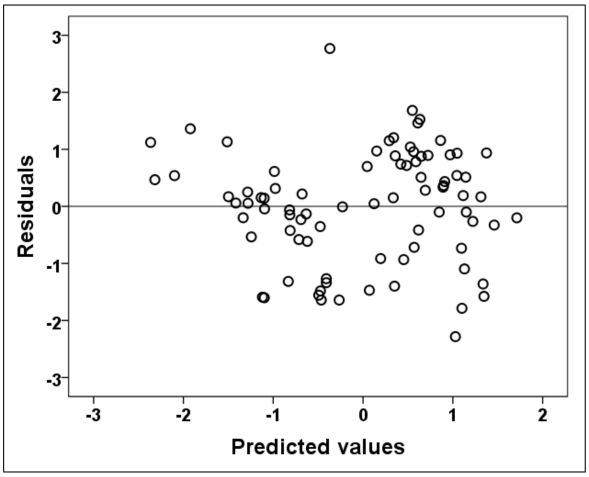


(a) Residuals plot-S&P500

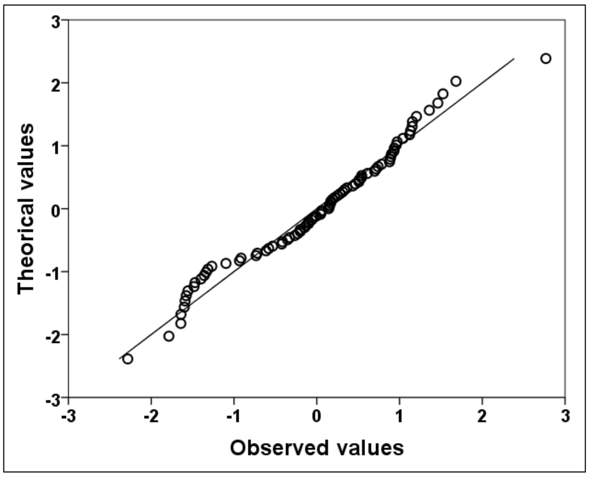


(b) Q-Q plot-S&P500

Fig. 11. Residuals normality and homoscedasticity for the S&P500 index (First period)

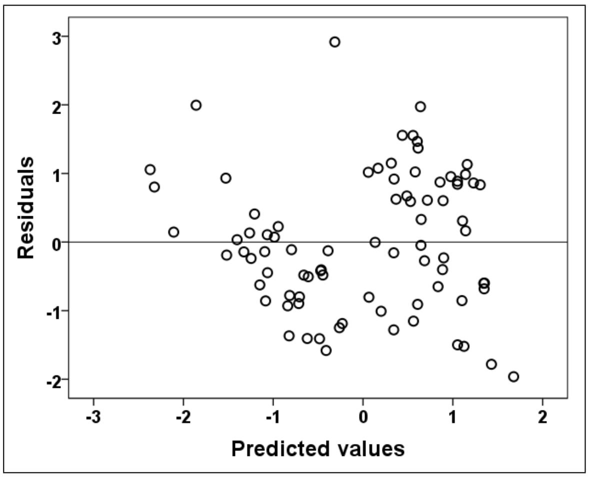


(a) Residuals plot-CAC40

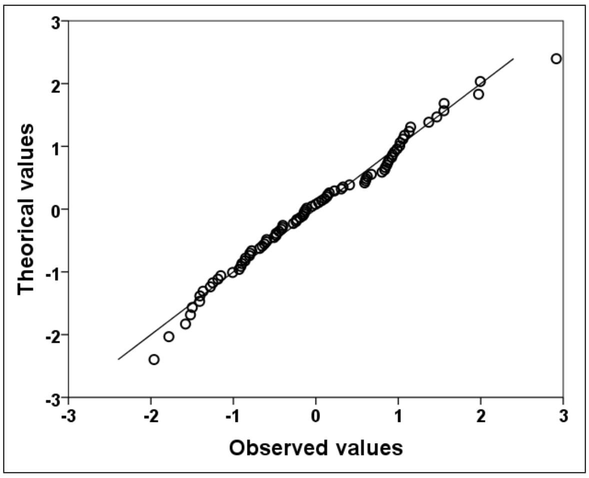


(b) Q-Q plot-CAC40

Fig. 12. Residuals normality and homoscedasticity for the CAC40 index (Second period)

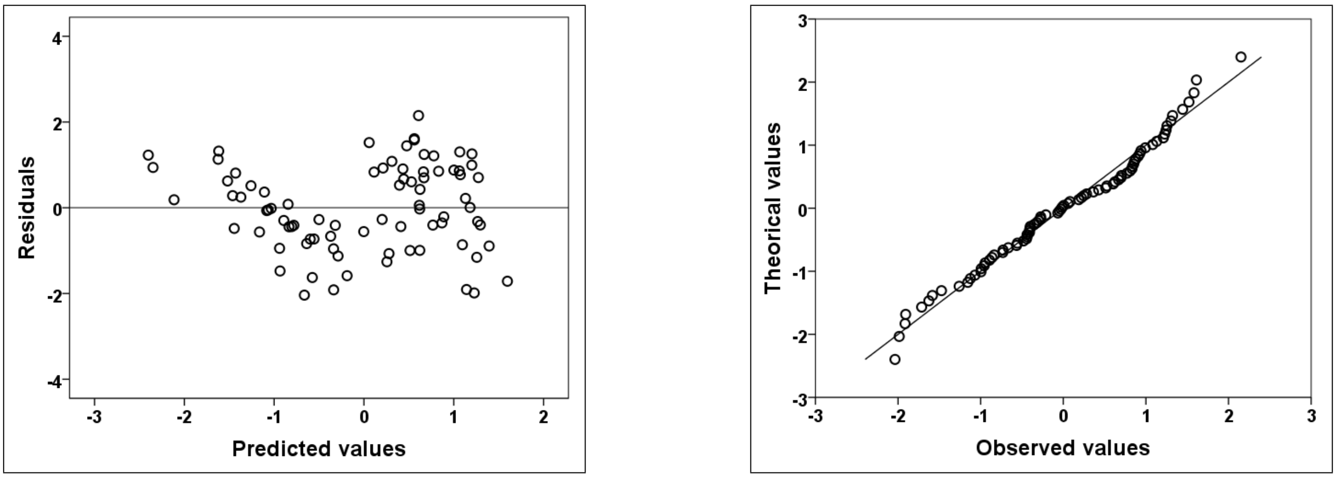


(a) Residuals plot-DAX30



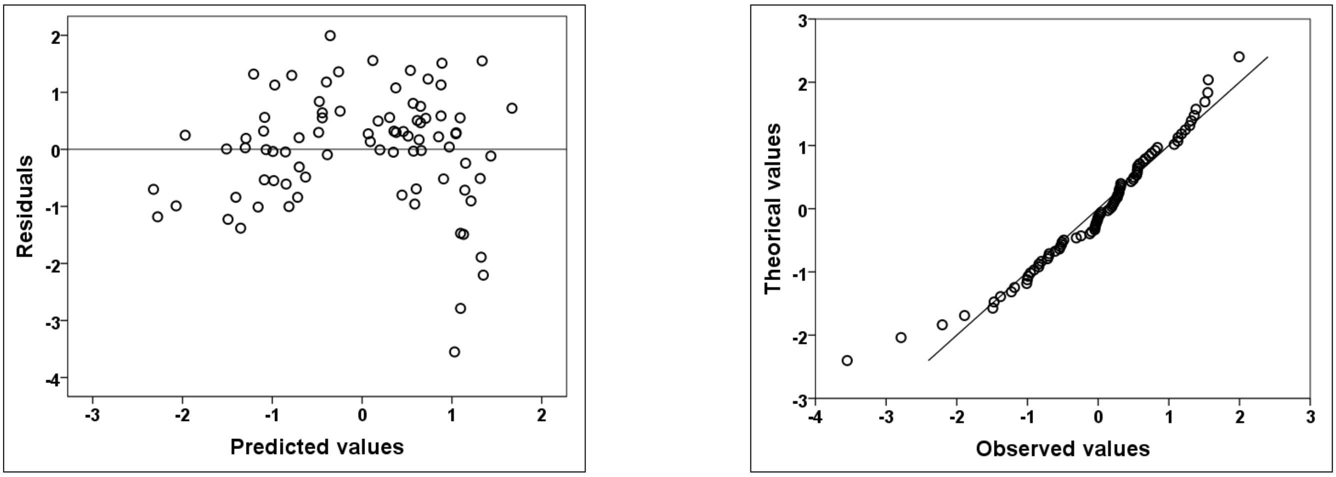
(b) Q-Q plot-DAX30

Fig. 13. Residuals normality and homoscedasticity for the DAX30 index (Second period-model1)



(a) Residuals plot-DAX30 (b) Q-Q plot-DAX30

Fig. 14. Residuals normality and homoscedasticity the DAX30 index (Second period-model2)



(a) Residuals plot-FTSE100 (b) Q-Q plot-FTSE100

Fig. 15. Residuals normality and homoscedasticity for the FTSE100 index (Second period)

[12] G. Bekaert, C.R. Harvey, and A. Ng, "Market integration and contagion," *Journal of Business*, vol. 78, no. 1, pp. 39–69, 2005.
[13] L.S. Junior and I.D.P. Franca, "Correlation of financial markets in times of crisis," *Physica A: Statistical Mechanics and its Applications*, vol. 391, no. 1-2, pp. 187–208, 2012.
[14] A. Moghaddam, M. Moghaddam, and M. Esfandyari, "Stock market index prediction using artificial neural network," *Journal of Economics, Finance and Administrative Science*, vol. 21, pp. 89–93, 2016.
[15] E. Guresen, G. Kayakutlu, and T. Daim, "Using artificial neural network models in stock market index prediction," *Expert Systems with Applications*, vol. 38, pp. 10 389–10 397, 2011.
[16] C. Liu, J. Wang, D. Xiao, and Q. Liang, "Forecasting s&p 500 stock index using statistical learning models," *Open Journal of Statistics*, vol. 6, no. 6, pp. 1067–1075, 2016.
[17] X. Jiawei and T. Murata, "Stock market trend prediction with sentiment analysis based on lstm neural network," *In: Proceedings of the International MultiConference of Engineers and Computer Scientists*, pp. 13–15, 2019.
[18] Ş. Sakaraya, M. Yavuz, A. Karaoğlan, and N. Özdemir, "Stock market index prediction with neutral network during financial crises: A review on bist-100," *Financial Risk and Management Reviews*, vol. 1, no. 2, pp. 53–67, 2015.
[19] Federal Reserve, Federal Reserve takes additional actions to provide up to $2.3 trillion in loans to support the economy, 2020.
[20] European Commission, Commission acts to make available 37 billion euro from the EU budget to address the Coronavirus, 2020.
[21] Z. Ge, W. Wang, and D. Chen,"Predicting Index Returns from the Market Structure Disagreement: Evidence from China," *Engineering Letters*, vol. 28, no. 4, pp. 1063–1074, 2020.