ISSN: 2658-8455
Volume 2, Issue 1 (January, 2021), pp. 100-108.
www.ijafame.org

Impact of the covid-19 crisis on the Moroccan stock market: Modeling the volatility of the M.A.S.I stock market index

Mohamed Beraich, ***(PhD in Finance)***
Faculty of Law, Economics and Social Sciences Agdal
Mohammed V University of Rabat
Morocco

Mohamed Amine Fadali, ***(PhD in Finance)***
Faculty of Law, Economics and Social Sciences Agdal
Mohammed V University of Rabat.
Morocco

Yousra Bakir, ***(PhD in Finance)***
Faculty of Law, Economics and Social Sciences Souissi
Mohammed V University of Rabat.
Morocco

Correspondence address: Faculty of Law Economics and Social Sciences Agdal
United Nations Avenue Agdal
Mohammed V University, Rabat.
Morocco
Zip code: 721
00212 5 37 77 27 32
mohamed.beraich87@gmail.com

Disclosure statement: Authors are not aware of any findings that might be perceived as affecting the objectivity of this study

Conflicts of interest: The authors reports no conflicts of interest.

Cite this article Beraich, M., Fadali, M. A., & Bakir, Y. (2021). Impact of the covid-19 crisis on the moroccan stock market: Modeling the volatility of the m.a.s.i stock market index. International Journal of Accounting, Finance, Auditing, Management and Economics, 2(1), 100-108. https://doi.org/10.5281/zenodo.4474606

DOI: 10.5281/zenodo.4474606

Published online: January 29, 2021.

ISSN: 2658-8455
Volume 2, Issue 1 (January, 2021), pp. 100-108.
www.ijafame.org

Impact of the covid-19 crisis on the Moroccan stock market: Modeling the volatility of the M.A.S.I stock market index

Abstract

The containment measures taken to combat the Covid-19 outbreak caused an economic and financial crisis at the international scale as well as at the national scale. The purpose of this article is to study and analyze the impact of this pandemic crisis on the Moroccan stock market and to show to what extent the containment decisions have negatively impacted the performance of the stock market. We proposed an approach that introduces the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to estimate the volatility of the Moroccan All-Share Index (MASI) caused by the uncertainty of the financial situation following the pandemic. The results show that during the study period, the value of the stock market index signaled a significant shock during the period of containment and a high volatility of its profitability, followed by a period of partial recovery after de-containment.

Keywords: Covid-19, Stock Market, Volatility, DCC-GARCH.
JEL Classification: G15, I10, C32.
Paper type: Empirical research

1. Introduction

The Covid-19 pandemic constitutes an economic shock, which would have major repercussions on the macroeconomic balance in 2020, pending a gradual and progressive recovery from 2021 onwards.

At the international level, all countries are trying to quantify the effects of the current Covid-19 health crisis on their economies and propose solutions. In this sense, research has been developed today in all fields and especially in economics to analyze the impact of this crisis and to forecast the future in order to take optimal decisions.

At the national level, this situation has been doubly weakened in 2020 by the effects of the drought recorded this year and by the halt of economic activity in several sectors following the containment measures to counter the pandemic.

The containment decision taken by the Moroccan government leads to a total or partial reduction in working hours, which automatically reduces the volume of production and the economic interactions that create wealth and allow the circulation of money.

This decision exacerbates the recession, on the one hand, but increases the well-being of the population, on the other hand, through a reduction in the number of contamination and deaths.

The epidemiological crisis has impacted all sectors of activity, just like the national financial market, which experienced a recession during the period of containment, accompanied by high volatility and large volumes, followed by a gradual recovery.

The Coordination and Surveillance Committee of Systemic Risks of the Moroccan Central Bank held weekly meetings at the headquarters of Bank Al-Maghrib (BAM) in Rabat to monitor and analyze the impact of the Covid-19 crisis on the national financial sector.

The idea here is to use the DCC-GARCH model developed by Engle [2002] to model the volatility of the MASI stock market index.

The basic hypothesis of this work is to show that containment decisions are likely to reduce the performance of the stock market index and increase the volatility of its return.

Using daily data over the period 01/10/2019 to 01/10/2020, we show how the decisions taken for the management of the health crisis affected the volatility of the Moroccan stock market and negatively impacted market liquidity by causing a depreciation of financial assets. Thus, investors lost confidence in the stock market, which then influenced the volatility of the stock market.

This article is organized as follows: the next section presents the literature review of our volatility estimation model, in the third section we will present section describes the model used to estimate volatility and the Moroccan financial market data used in our study. The results are then detailed in the fourth section. The last section concludes the paper.

2. Literature Review

The volatility of a financial asset is a measure of the variability in the distribution of the profitability of a financial asset over a given period. As such, it provides a measure of the risk of a financial asset. The greater the volatility is, the greater the variation in the value of the security is, and the greater the risk associated with investing in this asset is. It should be noted that this measure takes into account the variation in the price of the security without indicating whether this variation is positive or negative. According to Daly (1999), volatility can be defined as the variability of the variable under consideration. The more the variable fluctuates over a period of time, the more volatile it is assumed to be. Two types of volatility are generally cited: historical volatility and implied volatility. Historical volatility can be measured in a simple way with the standard deviation from the distribution of past returns of security. One can also calculate the implied volatility, which is defined as the forecast of the market volatility of financial security, under the assumption of market efficiency. Similarly, there are several methods and models for estimating the volatility of a security over a given past period in the financial literature. The Black-Scholes option pricing model (1976), gave a central role to the profitability volatility of the underlying asset in determining the value of an option. Changes in the underling's performance over a given period of time can be calculated and an estimate of its realized volatility can be obtained.

The ARCH (Autoregressive Conditionally Heteroskedastic Autoregressive) models introduced by Engle (1982) are based on an endogenous parameterization of the conditional variance and allow this type of property to be taken into account. The ARCH model was proposed by Engle (1982), is based on an endogenous parameterization of the conditional variance and takes into account the fact that volatility evolves stochastically.

Bollerslev (1986) developed Engle's model to propose the GARCH model, which has been widely used in the financial literature to estimate the volatility of financial security over time.

Bollerslev, Chou and Kroner (1992) presented a broad review of the literature using the GARCH model to model the volatility of financial variables such as the inflation rate, the interest rate, the exchange rate, and so on. Sufficient regularity conditions to obtain convergence and asymptotic normality properties were established in the case of (linear) ARCHs by Weiss (1984) and (1986) (see also Bollerslev and Woolridge (1990) for a more general class). The most constraining of these (rarely verified in practice...) is a condition of the existence of the moment of order 4. Lumsdaine (1990) shows that it is possible to free oneself from this constraint in the

GARCH (1,1) case.

In 2001, Engle and Sheppard introduced the DCC-GARCH model , which is an extension of the CCC-GARCH model, for which the conditional correlation matrix is designed to vary over time. In this thesis the implementation of the DCC-GARCH model will be considered, using Gaussian, Student t- and skew Student t-distributed errors.

The subprime crisis in 2007 and the fall of the stock markets led the world economy into an unprecedented financial panic that is still unfolding.

Advocates of the classical theory have pointed out that the excessive volatility of stock market indices compared to that of dividends can be explained by the volatility of the discount rate (Fama, 1991, Cochrane, 2011). Moreover, they have argued against excessive volatility tests that can only be performed with underlying models: if the volatility of stock market indices is found to be excessive in relation to dividend forecasts or the evolution of consumption, the models used to make dividend forecasts or to link the price of financial assets to consumption may be wrong. The question of whether financial market volatility is excessive to be attributed to fundamentals is still debated today. Recently, researchers have found a significant influence of the business cycle on the low-frequency component of volatility, while abrupt increases in volatility may be partly due to shifts in market sentiment (Adrian and Rosenberg, 2008; Engle and Rangel, 2008; Engle et al., 2013; Corradi et al., 2013; Chiu et al., 2018).

In our study, we will use a DCC-GARCH model when clusters of volatility are observed, i.e. periods of low volatility and periods of high volatility.

3. Methodology

To study the impact of COVID-19 on the MASI stock market, we estimate the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity model (DCC-GARCH) suggested by Engle (2002) using a daily series of MASI market indexes prices between 01/10/2019 and 01/10/2020.

3.1. Research model

This part is devoted to the presentation of the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models.

ISSN: 2658-8455
Volume 2, Issue 1 (January, 2021), pp. 100-108.
www.ijafame.org

These models do not impose a constant volatility of a particular asset, which can be low in some periods and high in others. These models are all attempted to measure these temporal variations in volatility.

The ARCH processes also aim to account for the fact that the conditional variance is not constant and proposes a way to estimate it based on the square of the returns. From what has just been said, we will treat this class of model with suspicion: it is possible that volatility is not constant over time, but that an ARCH model or their GARCH generalization do not capture this effect, or even conclude in some cases that there is no temporal dependence in the returns.

The ARCH and GARCH models and their main properties are presented below.

The models were initially proposed by Engle (1982) and Bollerslev (1986), Tim Bollerslev being Robert Engle's PhD student. The first model was Engle's, and aimed to obtain a model of the conditional variance of inflation (month-to-month) for Great Britain. ARCH (1) model is of the form:

$$\begin{cases} x_t = \sqrt{h_t}\varepsilon_t \\ h_t = \omega_0 + \omega_1 x_{t-1}^2 \end{cases}$$

With:
$\varepsilon_t \sim N(0,1)$;
h_t represents the conditional variance of the processx_t;
ω_0 and ω_1 are the parameters of the ARCH model.

For many applications, the introduction of a large number of p lags in the conditional variance equation of the ARCH model (p) is necessary to account for the long memory of volatility that characterizes some monetary and financial series. This large number of parameters can lead to the violation of the non-negative variance constraint and pose estimation problems. In this perspective, an important extension, the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH), is suggested by Bollerslev [1986]. The GARCH (p,q) process is a form of ARMA model on conditional variance. This approach requires fewer parameters to be estimated than the ARCH (p) formulation to model shock persistence phenomena. The conditional variance of the variable under study is determined by the square of the p past error terms and the q lagged conditional variances.

Volatility persistence is greater in the GARCH model because of the addition of a recurrence relationship between the current conditional variance and those of the q previous periods. The comparison between the GARCH (1.1) and ARCH (8) models shows that the GARCH (1.1) process gives a better fitted regression value, since a GARCH model with very few parameters fits as well as an ARCH model with many parameters to estimate, since GARCH (1.1) model implies an ARCH model because it has the advantage of being more parsimonious.

Moreover, Bolleslev(1986) demonstrates that the GARCH process is by construction, capable of capturing thick distribution tails even if the conditional distribution of standardized innovations follows a normal law. All models in the ARCH family share this characteristic, but it is often the case that innovations are sometimes more leptokurtic than a GARCH (p,q) model with a normal distribution of yields would allow. Bollerslev (1987) notes that the use of a Student-t distribution with thicker distribution tails than the Gaussian distribution can potentially solve this problem. Knowing that the parameters of a GARCH model must be positive to ensure that the conditional variance is always positive.

A GARCH(p,q) process is noted as follows :

$$x_t = \sqrt{h_t}\varepsilon_t$$
$$h_t = \omega_0 + \sum_{i=1}^{p} \alpha_i x_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$$

With :
$\varepsilon_t \sim N(0,1)$;
h_t represents the conditional variance of the process x_t;
ω_0,$\alpha_i$and $\beta_j$are the parameters of the GARCH model.

The process GARCH (1,1) is noted as follows :

$$x_t = \sqrt{h_t}\varepsilon_t$$
$$h_t = \omega_0 + \alpha_1 x_{t-1}^2 + \beta_1 h_{t-1}$$

The Dynamic Conditional Correlation (DCC-GARCH) belongs to the class ‘Models of conditional variances and correlations’. It was introduced by Engle and Sheppard in 2001. The model is built on the idea of modelling the conditional variances.

The process DCC-GARCH (1,1) is noted as follows:

$$h_t = \omega_0 + \alpha_1 \epsilon_{1,t-1}^2 + \beta_1 h_{t-1}$$

3.2. Data

In this article, we study the impact of the health crisis on a daily series of MASI market indexes prices between 01/10/2019 and 01/10/2020, i.e. 252 observations.

Because stock markets are closed on weekends and holidays, non-working days are therefore not taken into account.

The data of our study are taken from the following website:

"http://www.casablanca-bourse.com/bourseweb/index.aspx#"

Why was this period chosen?

Based on the international experience in the fight against the covid-19 virus, the Moroccan authorities decided to implement a general containment throughout the country from March 16, 2020 to reduce the number of contamination throughout the containment, this decision had an undesirable impact on the performance of the Moroccan stock market.

Our database covers three remarkable sub-periods:

- Before containment.
- During containment.
- After containment

4. Results and discussions

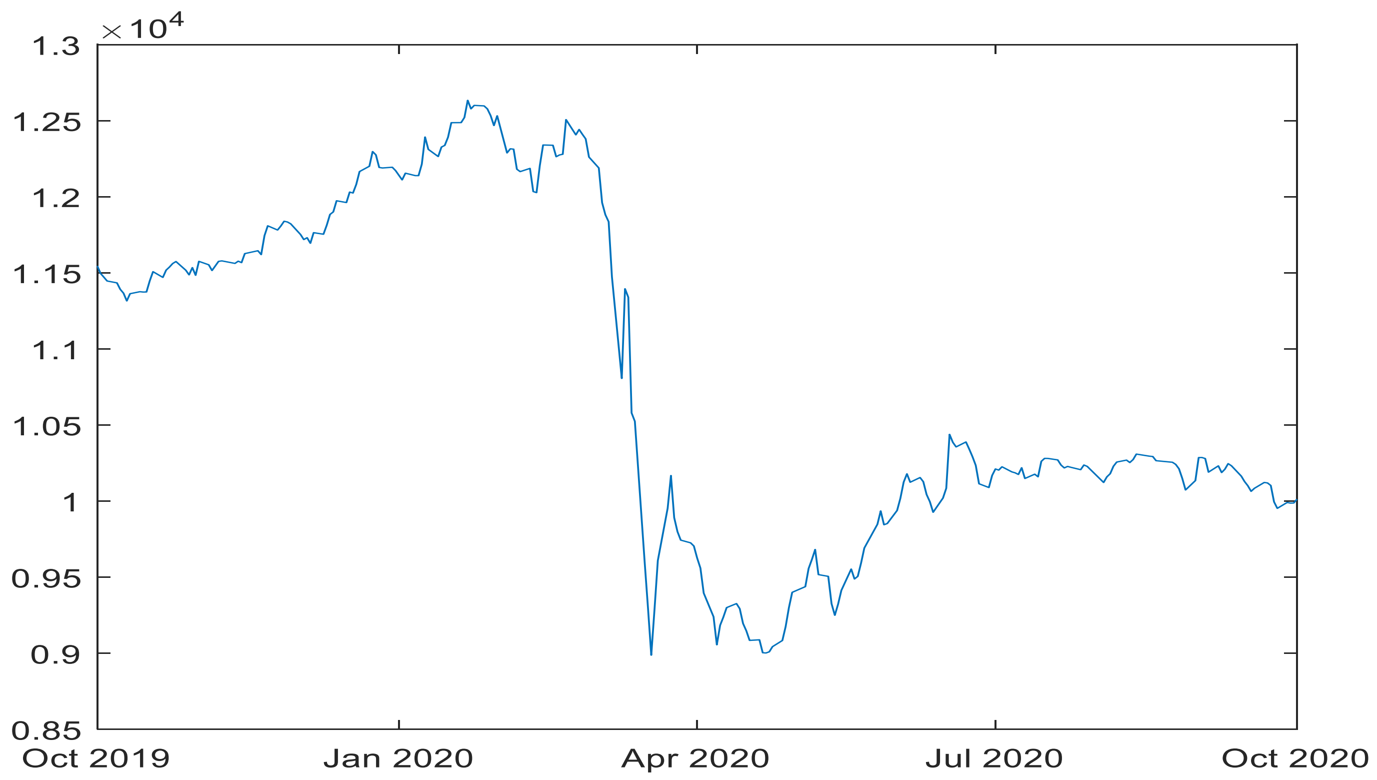
4.1. Graphic analysis

The first studies on the probability distribution of stock market prices were based on the normal distribution, or Gauss' distribution. The normal hypothesis, therefore, implies that the Gaussian distribution best models relative changes in stock index returns, stock prices or exchange rates. In order to test this hypothesis of normality, skewness and kurtosis were used. In principle, the results obtained should be close to the assumptions commonly made in financial theory.

Figure 1 shows the daily closing prices of the MASI stock market index in the period from 01/10/2019 to 01/10/2020 (i.e. 252 observations).

Since the stock markets are closed on weekends and holidays, non-working days are, however, not taken into consideration.

Figure 1: evolution of the closing price of the MASI index from 01/10/2019 to 01/10/202



Source: *Authors*

A look at the following graph reveals to us that there is no stationarity.

- A trend break.
- Volatility that varies over time.

Figure 1 shows the change in the value of the market index over the study period. It is characterized by an increasing trend during the last quarter of 2019 (before confinement) followed by a sharp decline in the middle of the period at the end of March and the beginning of April starting in March (beginning of confinement) to reach a peak to vary another time until the end of the study period with a partial gradual recovery starting in May.

This data (the daily closing prices) were transformed, allowing us to study the series of achievable yields.

Under the hypothesis of no-stationarity of the process, we first differentiate by going through the calculation of the yields, then we examine the correlogram of the differentiated series.

There are many measures of return of a stock index, the one frequently used is the geometric return or log-return, which consists in calculating the logarithm of the differential of the values in t and t - 1 :

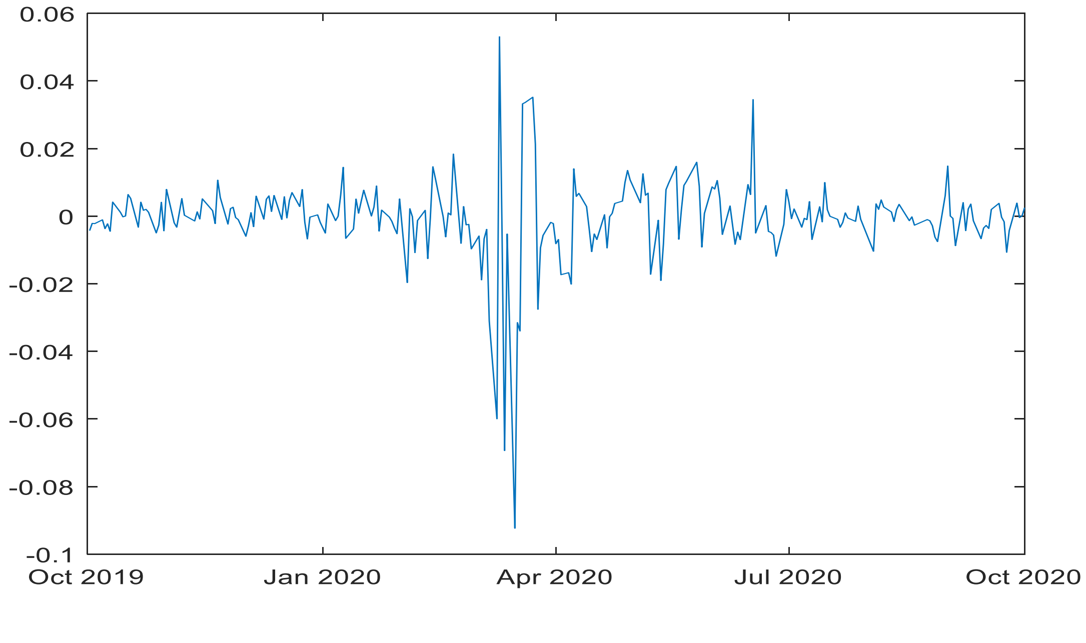
Definition: "Log-return".

Let Pt be the price of security at time t, then we define the yield of this security at time t by:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right), \qquad t = 1, 2, \ldots$$

Figure 2 shows the evolution of the MASI index return series from 10/31/2019 to 10/31/2020, with the x-axis showing the number of observations (i.e. working days) and the y-axis showing the daily index return. The first observation that can be made is that the series is stationary, but there are still periods of strong variation. The second is the existence of some extreme values.

Figure 2: Series of MASI Index Returns in Percent from 10/01/2019 to 10/01/2020.



Source: *Authors*

ISSN: 2658-8455
Volume 2, Issue 1 (January, 2021), pp. 100-108.
www.ijafame.org

Analyzing Figure 2, we notice that the profitability of the market index recorded a low volatility in the last quarter of 2019 and the beginning of 2020 followed by a period of high volatility at the end of the first quarter of 2020, which corresponds to the period of the beginning of containment.

From June onwards, it can be seen that the level of fluctuations in the market return began to decrease after the gradual deconfinement and recovery of economic activity.

4.2. Descriptive statistics

Table 1: Statistics of the MASI Index Return Series from 10/31/2019 to 10/31/2020.

Mean	-0.031526
Mediam	-0.020000
Maximum	5.450000
Minimum	-8.820000
Standard Deviation	1.235669
Skewness	-1.995889
Kurtosis	19.29132
Jarque-Bera	2918.918
Probability	0.000000

Source: *Authors*

Table 1 shows the various statistical characteristics of the MASI return series over the period studied. The first finding in this table is that the MASI return series has a distribution of :

leptokurtic: the flattening coefficient (kurtosis k= 19.29132) is greater than 3, that of the normal distribution and the skewness coefficient (skewness s = -1.995889) is different from zero.

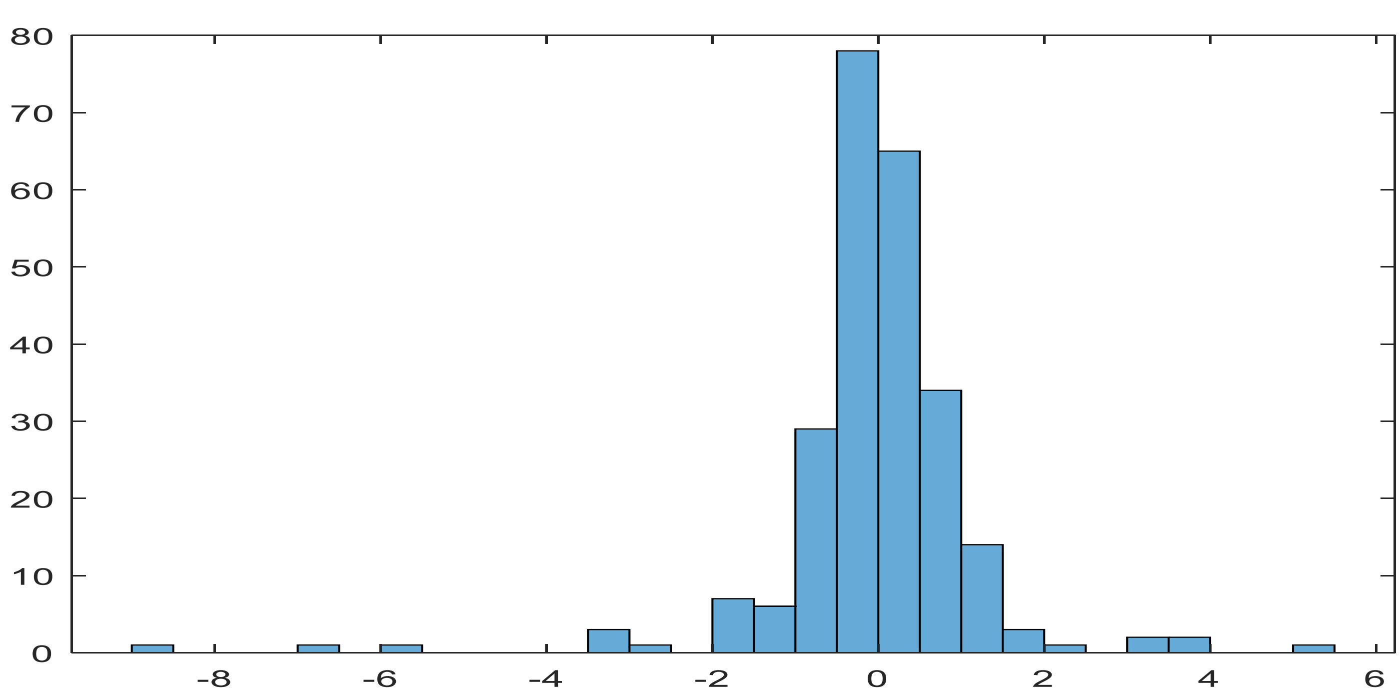
The analysis of skewness and kurtosis leads to the usual conclusions in stock price studies. They are different from 0 and 3, which means that the distribution is not normal but rather asymmetric with thick tails characterizing a leptokurtic distribution. This leads us to reject the hypothesis of normality.

These properties can be summarized in Figure 3, which represents the histogram of the return series, by sharing the daily returns of the MASI index. It is clear that the empirical distribution of returns is not normally flattened. In particular, it has a very thick tails (kurtosis greater than 3).

Additionally, the JarqueBera test gives a result of 2918,918 and a p-value equal to 0.000000 (The p-value is the probability, under H_0, of obtaining a statistic as extreme (not to say as large) as the value observed in the sample. The p-value at a predefined threshold (traditionally 5%). If the p-value is below this threshold, the null hypothesis H_0 is rejected.

In our case p-value < 5% , therefore, we reject H_0: the data follow a normal law) practically null. This leads us to confirm the rejection of normality.

Figure 3: Histogram of the MASI Index Return Series from 10/31/2019 to 10/31/2020



Source: *Authors*

4.3. Econometric analysis

The variance of the yield series changes over time. To demonstrate this important nature of yield series, it is interesting to subdivide the data series and then compare the standard deviation ((i.e. $S = \sqrt{\text{var}(X)}$) of each of the sub-series obtained.

Table 2: standard deviations of the MASI index return series in (%) for different periods of containment.

Period	Standard deviation
from 01/10/2019 to 15/03/2020 (before containment).	1,18
from 16/03/2020 to 10/06/2020 (during containment).	1,82
from11/06/2020 to 01/10/2020 (aftercontainment).	0,62

Source: *Authors*

For analyzing Table 2, it is evident that the series of returns of the MASI index for the pre-containment period from October to the middle of March 2020 recorded a low standard deviation of 1.18% and, therefore, the volatility is lower. For the periods before and during the confinement the market reported a high volatility reaching 1.82% between 16/03 and 10/06/2020. After the end of the containment, the value of the market volatility decreased to lower levels than those recorded during the containment. The volatility after the confinement reached 0.62% in the period between 11/06/2020 and 01/10/2020.

The results obtained in Table 2 affirm the hypothesis of non-constant volatility (volatility cluster).

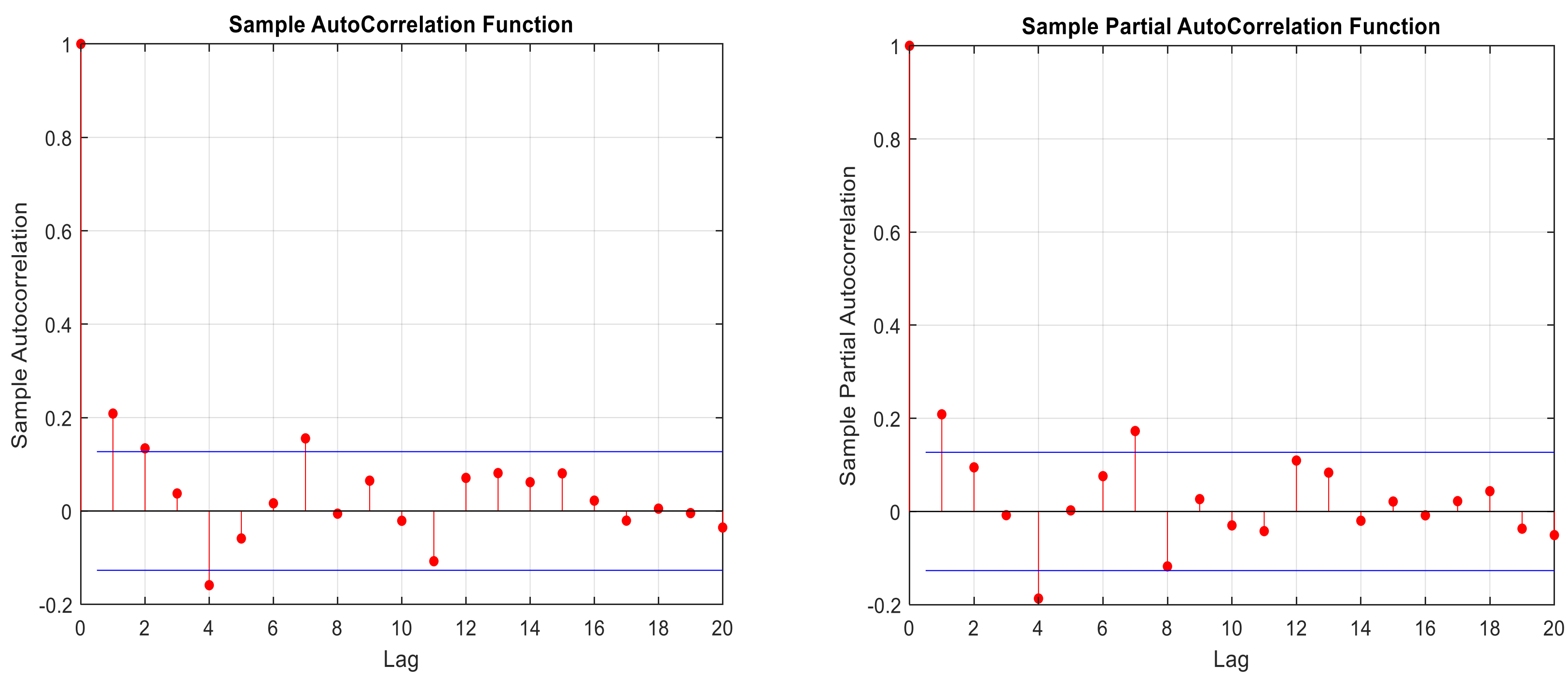
Indeed, our series does not have a constant variance (standard deviation squared), which, therefore, demonstrates the existence of a certain Heteroskedasticity.

In order to verify this result, it is necessary to look at the autocorrelation functions (simple and partial correlograms) for the MASI return series.

The returns show the presence of autocorrelation (Figure 4), while the squares of the returns are not autocorrelated at a significant level (Figure 4).

This leads us to reject the hypothesis of the absence of the price autocorrelation and highlights the presence of Heteroskedasticity.

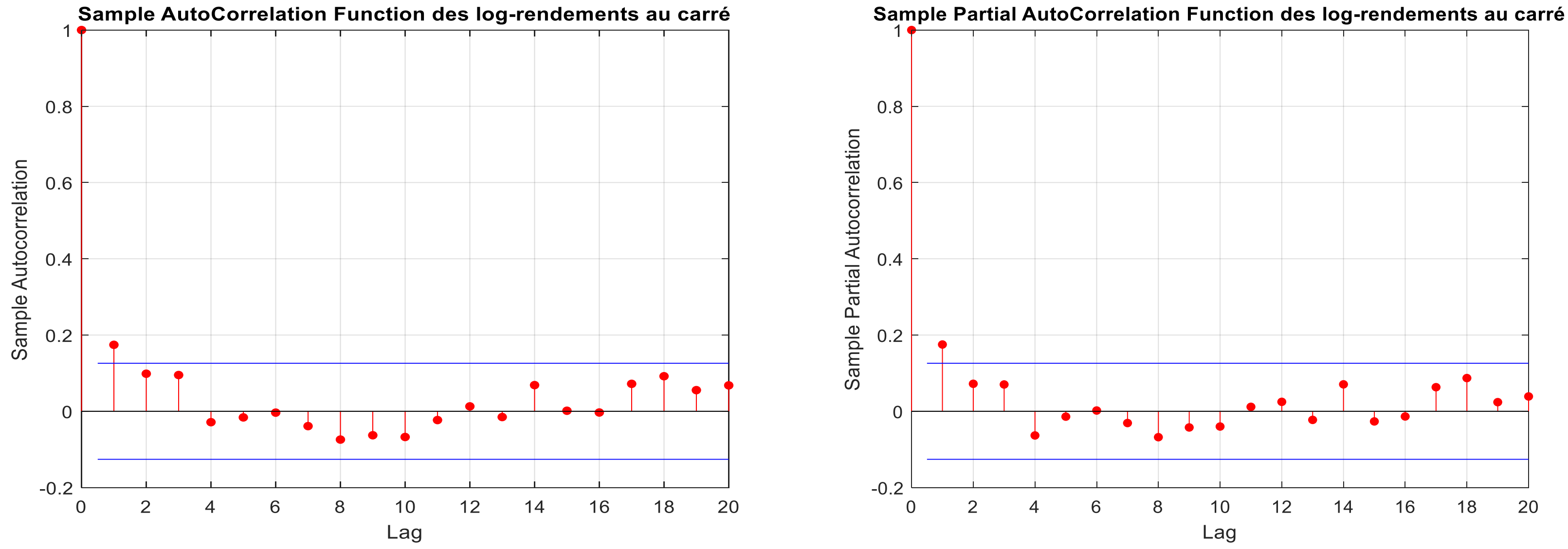
Figure 4: Autocorrelogram of the MASI Return Series



Source: *Authors*

If a series is strict white noise (i.e. there is no significant autocorrelation), and so are the series deduced from the square. However, we clearly notice the presence of a weak dependence of these variables on each other, which is translated into lasting insignificant autocorrelations for the yield squared series (Figure 5).

Figure 5: Autocorrelogram of the MASI Return squares



Source: *Authors*

Globally, the white noise hypothesis is rejected. So, we will have to think about other types of modeling. Thus, ARMA models seem unable to model this series and take into account the phenomenon of heterosedasticity.

In this respect, Engle proposes in 1982 the ARCH (Auto Regressive Conditionally Heteroskedastic) models which will be generalized in 1986 by GARCH (Generalized Auto Regressive Conditionally Heteroskedastic).

In this section, we have presented some characteristics of the performance series. Among these characteristics are the excess flattening coefficient, the skewness coefficient, as well as the Heteroskedasticity and autocorrelation in the yield series. We have shown the techniques, either visual or statistical, used to verify the presence of Heteroskedasticity.

4.4. DCC-GARCH estimation

Volatility is an indicator of the variability of financial security's performance. It is considered a parameter for quantifying the risk associated with fluctuations in the price of a financial asset. When volatility is higher, the risk of loss is also higher.

Table 3 shows that all coefficients of the DCC-GARCH model (1,1) are significant (Probability<5%).

ISSN: 2658-8455
Volume 2, Issue 1 (January, 2021), pp. 100-108.
www.ijafame.org

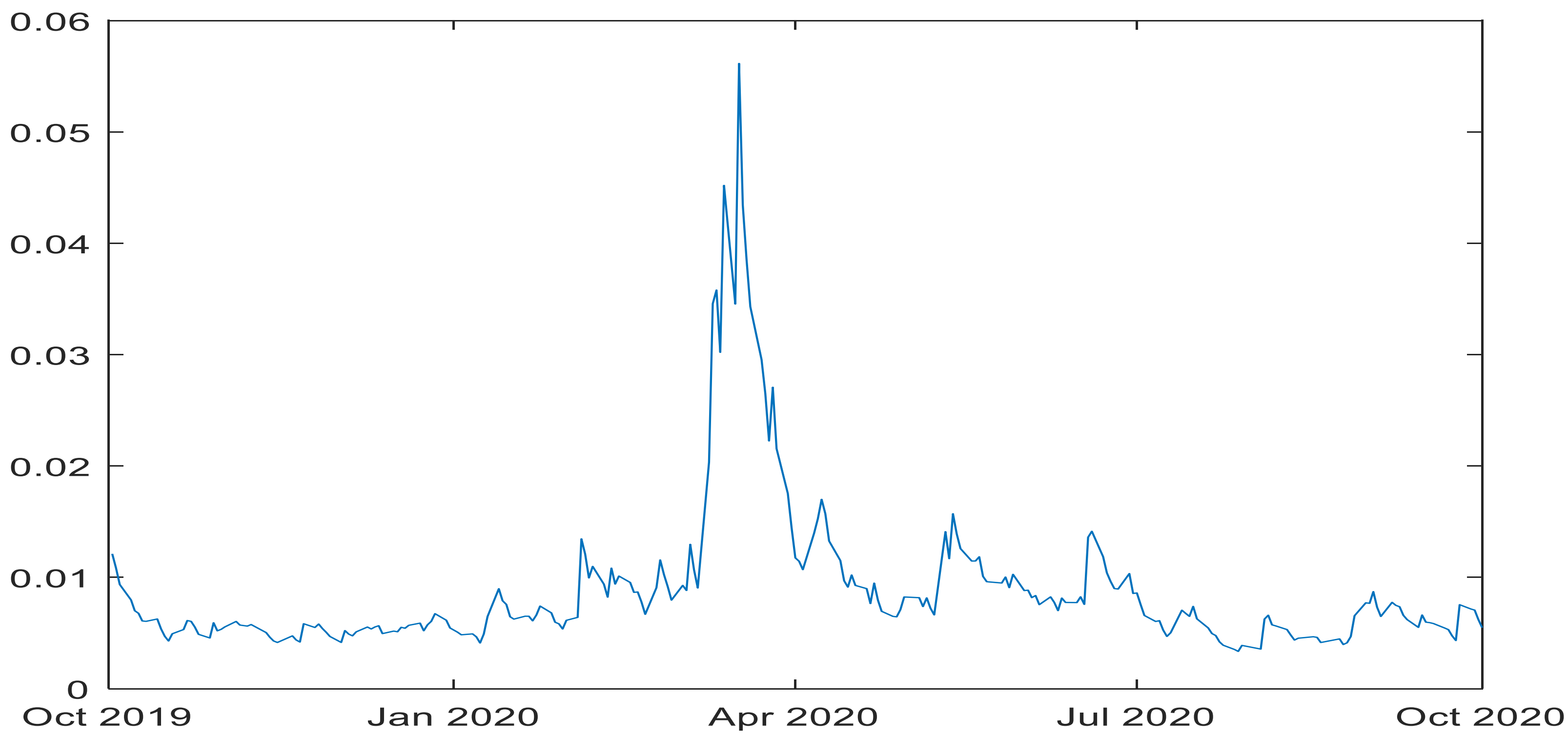
Table 3: DCC-GARCH (1,1) estimation

Parameter	Value	Standard-error	t-statistic	probability
Constant ω_0	0.00004367	0.00002319	2.1250	0.0175
α_1	0.6271	0.0073	8.9731	5.237×10^{-18}
β_1	0.51873	0.0251	4.7381	4.211×10^{-8}

Source: *Authors*

In Figure 5 below, we illustrate the conditional volatility of market returns using the DCC-GARCH model (1.1).

Figure 5: conditional volatility of the MASI Return Series



Source: *Authors*

From Figure 5, which presents the evolution of conditional volatility modeled using a DCC-GARCH (1,1), we can see that the volatility recorded a significant increase in the middle of the period studied in our article, which corresponds to the period of confinement.

This upward trend in the variability of returns on our financial assets can be seen by a simple visual analysis of the series of returns presented in Figure 2.

We can also confirm this strong fluctuation in volatility by analyzing Figure 1, which illustrates the decline in the value of the MASI stock index over the same containment sub-period.

The fact is that, as the expected, volatility rises persistently. It further reinforces or accentuates agents' demands and sensitivities about the expected returns on their future investments.

5. Conclusion

The Covid 19 pandemic hit a large part of the world and had a strong impact on the world economy, so the first half of the year 2020 was marked by a crisis unprecedented in its nature and the extent of its consequences.

The international stock markets experienced a significant drop in their prices, and the major stock market indices such as the CAC40, DAX and FTSE recorded a historic fall and a significant fluctuation in their values.

The MASI index fell by 28.14% during the period of containment, this decline was nevertheless followed by a phase of partial recovery after the containment, this recovery has been supported by the European Financial Markets Authority, which in June 2020 gave a positive rating to the Moroccan stock market, this rating will allow European companies to conclude transactions on the Casablanca Stock Exchange.

Following the official announcement of the health crisis in the Kingdom and the drastic measures taken by the public authorities encouraging a mandatory containment, the Moroccan stock market has recorded a significant decline leading to a counter-performance which has a negative impact on the valuation of portfolios of all categories of investors and deteriorates the liquidity of the financial market.

Volatility is linked to this liquidity factor. In an illiquid market, quotations may remain unchanged over a certain period of time due to the absence of transactions. In this case, low volatility should not be interpreted as a low market risk, but as a high liquidity risk. On the other hand, in an illiquid market, large price fluctuations may be necessary for a transaction offer to find a counterpart. In this case, high price volatility is due to this lack of liquidity, and not to a change in the fundamental value of the assets. In other words, the liquidity factor may be fundamental in interpreting volatility (Bank of French, 2003).

We have empirically observed that large fluctuations in returns are followed by small variations and that small variations are followed by large variations. We have also observed a clustering of extremes into clusters or packages of volatility. This type of phenomenon calls into question the hypothesis of Homoskedasticity (constancy of volatility). This clustering of volatility in packets is essentially due to the correlations of financial series. Because of this correlation, a large movement corresponding to high volatility is likely to be followed by a movement of the same magnitude, and the same applies to a movement of small amplitude (Engle, 1982). Several models have been proposed to model and describe the volatility process. The best known are the GARCH models that are the subject of our research, which introduces past volatility as explanatory variables for volatility at the present time.

In our study, we have modeled the volatility of the Moroccan stock market through its MASI index during the covid-19 crisis. Using a DCC-GARCH model (1,1), we showed that changes in the volatility of the Moroccan stock market index are due to the containment measures and the state of emergency launched by the Moroccan authorities in the second quarter of 2020, after a near stability of this volatility at the end of 2019 and the first months of 2020. These decisions provide bad news about the liquidity conditions facing financial institutions and the Moroccan stock market, increasing financial market volatility in the face of high uncertainty about the future of investments. This effect is being experienced not only in the Moroccan market but in international markets as a whole.

The deconfinement decision taken gradually from June 2020 had a positive impact on the market, and the MASI stock index recorded a partial recovery in its performance, and the degree of variability in its profitability as measured by conditional volatility declined relative to the period of containment.

References

(1) Andersen T. G., Bollerslev, T., Christoffersen, P. F. & Diebold, F. X. (2005). Volatility forecasting. NBER working paper No. 11188.
(2) Andersen T. G., Bollerslev, T., Christoffersen, P. F. & Diebold, F. X. (2006).Volatility and correlation forecasting.Handbook of Economic Forecasting, NorthHolland : Amsterdam, pp. 777- 878.
(3) Bauwens, L. et Giot, P. (2001). Econometric Modelling of Stock Market Intraday Activity, Advanced Studies in Theoretical and Applied Econometrics, Kluwer : Dordrecht.
(4) Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307-327.
(5) Brownlees, C. T., Cipollini, F. et Gallo, G. M. (2011). Multiplicative error models. Econometrics Working Papers Archive 2011_03.
(6) Chou, R. Y. (2005). Forcasting financial volatilities with extreme values : The conditional autoregressive range (carr) model. Jounal of Money, Credit and Banking 37, 561-582.
(7) Cipollini, F. et Gallo, G. M. (2010). Automated variable selection in vector multiplicative error models. Computational Statistics & Data Analysis 54, 2470-2486.
(8) Cipollini, F., Engle, R. F. et Gallo, G. M. (2012).Semi parametric vector mem. Journal of Applied Econometrics, doi :10.1002/jae.2292.
(9) Colletaz G. (2002) .Condhet.src : Estimation of ARCH models with RATS, Research paper LEO, -24.
(10) D. De Walque, J. Friedman, R. Gatti, A. Mattoo, (2020).How Two Tests Can Help Contain COVID-19 and Revive the Economy.
(11) Engle, R. F. (2002). New frontiers for ARCH models. Journal of Applied Econometrics 17, 425-446.
(12) Engle, R. F. et Gallo, G. M. (2006). A multiple indicators model for volatility using intra-daily data. Journal of Econometrics 131, 3-27.
(13) Engle, R. F., Gallo, G. M. et Velucchi, M. (2012).Volatility spillovers in East Asian financial markets : a MEM based approach. The Review of Economics and Statistics 94, 222-233.
(14) Goodell, J. W. 2020. COVID-19 and finance: Agendas for future research, Finance Research Letters.
(15) Nielsen O. E., Hansen, P. R., Lunde, A. & Shephard, N. (2008). Designing realised kernels to measure the ex-post variation of equity prices in the presence of noise. Econometrica 76, 1481-1536.
(16) Shumway, R. M. et Stoffer, D. S. (2006). Time Series Analysis and Its Applications, with R Examples, second edition, Springer: New York.
(17) Tsay, R. S. (2010). Analysis of Financial Time Series, Wiley : New York. 87
(18) Zakaria. F. (2020). The COVID-19. macroeconomics scenarii and role of containment in Morocco journal. One health. 10 p 100-152
(19) Zakaria.F (2016). Financial stability report: lessons from the central banks, Archives of Business Research.