HEC MONTRÉAL

The impact of COVID-19 on S&P 500 in 2020

par

Neda Assadi

Simon van Norden

HEC Montréal

Directeur de recherche

Sciences de la gestion

(Spécialisation en finance)

Mémoire présenté en vue de l'obtention

du grade de maîtrise ès sciences en gestion

(M. Sc.)

Août 2023

Résumé

En février 2020, la pandémie a provoqué d'importantes perturbations sur les marchés financiers mondiaux. La forte volatilité au cours de cette période a entraîné des changements impressionnants dans la valeur des actions. Des études antérieures, comme celles d'Alain et al. (2020) et Acharya et al. (2020), ont enquêté sur la volatilité du marché au cours de la première vague du choc COVID-19 et observé une augmentation de la volatilité du marché. Notre analyse porte sur l'impact du COVID-19 sur l'indice financier S&P 500 durant la première année de la pandémie, incluant les deux vagues du virus.

En nous inspirant des études d'Alain et al. (2020), nous rassemblons les données journalières liées à la COVID-19 disponibles sur OxCGRT. Notre étude révèle que malgré qu'au début de 2020, la COVID-19 ait joué un rôle important dans la volatilité de l'indice, cette tendance n'a pas été constante tout au long de l'année.

Dans cette recherche, nous nous basons sur les mesures de « nouvelles » liées à la COVID-19, reconnaissant l'importance des attentes du marché. Le modèle ARIMA est utilisé pour construire des erreurs de prévision, utilisées comme des « effets de nouvelles » dans le test de style LM (test de score) pour détecter des corrélations entre la COVID-19 et le rendement de l'indice S&P 500. Tenant compte des effets de levier et de la non-normalité, nous utilisons le modèle GJR-t-GARCH, sachant que ces facteurs peuvent influencer le comportement du marché pendant les périodes d'extrême incertitude comme celles vécues pendant la pandémie de COVID-19.

Mots clés : pandémie, marchés financiers américains, krachs, volatilité, S&P 500, COVID-19

Méthodes de recherche : modèle ARIMA, modèle GJR-t-GARCH (modèle GARCH à seuil), Test du multiplicateur de Lagrange (test de score)

Abstract

In February 2020, the COVID-19 pandemic caused significant disruptions in the global financial markets, resulting in high volatility and notable changes in stock values. Several previous studies, including those by Alain et al. (2020) and Acharya et al. (2020), investigated the market volatility during the initial wave of the COVID-19 shock and observed a substantial increase in market volatility. Our research focuses on examining the impact of COVID-19 on the S&P 500 financial index throughout the first year of the pandemic, encompassing the two waves of the virus.

In line with the studies conducted by Alain et al. (2020), we gathered daily data regarding COVID-19 from the OxCGRT database. Our analysis revealed that while COVID-19 significantly influenced index volatility in early 2020, this trend did not persist throughout the entire year.

To conduct our research, we utilized "news" measures related to COVID-19, as we recognized the importance of market expectations. Employing the Autoregressive Integrated Moving Average (ARIMA) model, we generated forecast errors, which we employed as "news effects" in an LM-style test (score test) to identify correlations between COVID-19 and the performance of the S&P 500 Index.

Considering factors like leverage effects and non-normality, we employed the Glosten-Jagannathan-Runkle-t-Generalized Autoregressive Conditional Heteroskedasticity (GJR-t-GARCH) model. We acknowledged that these factors could influence market behaviour during periods of extreme uncertainty, such as those experienced during the COVID-19 pandemic.

Keywords: pandemic, US financial markets, crashes, volatility, S&P 500, COVID-19

Research methods: ARIMA model, GJR-t-GARCH model (GARCH threshold model), Lagrange multiplier test (score test)

Table of contents

Résumé iii

Abstract v

Table of contents vii

List of figures and tables ix

List of abbreviations and acronyms xi

Acknowledgements xiii

1. Introduction 1

2. The era of COVID and uncertainty 5

 2.1 Proxy variables 5

 2.2 Expectations and their influence on the Volatility in the Market 6

3. Data 9

4. Methodology 11

 4.1 Modeling S&P 500 daily returns during COVID 11

  GARCH models 11

  GJR-GARCH model 11

  GARCH.X 12

 4.2 COVID News and ARIMA models 13

  ARIMA models 13

  ARIMA Model Parameters 13

  Seasonal ARIMA 14

 4.3 Measurement of model performance 14

 4.4 The expanding window estimation of the ARIMA models 15

  Rolling forecasts with expanding windows 15

4.5 LM Tests for Additional Variables ... 15

5. Results and analysis ... 17

5.1 Variables ... 17

5.2 Rolling forecasts ... 19

5.3 LM style testing ... 20

5.4 Residuals of the GJR-t-GARCH and its conditional variance ... 21

5.5 Regressing the US residuals on forecast errors ... 23

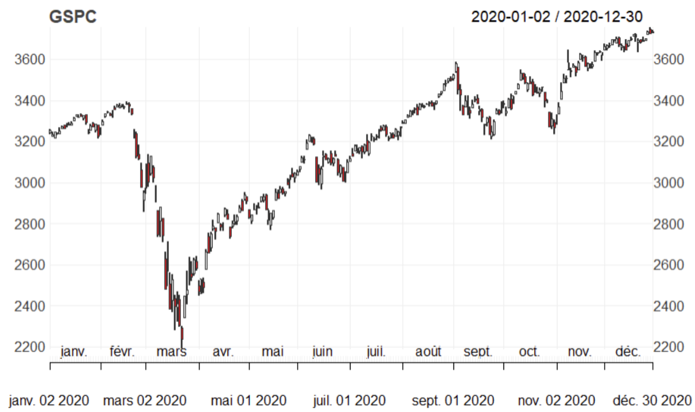
5.6 Regressing the standardized residuals on forecast errors ... 24

6. Conclusion ... 25

Bibliography ... 29

Appendix ... i

List of figures and tables



List of figures

Figure 1: the S&P 500 returns in 2020 during the first year of COVID-19……….………….1

Figure 2: the US index return's variations during the first year of the pandemic……………...17

Figure 3: the variations of selected COVID variables in 2020……………………………....18

Figure 4: the rolling 7-day ahead forecasts for time t of our four selected variables…………..19

Figure 5: positive rates and stringency index series including the 7 days forecasts for the last week of the year……………………………………………………………………………….20

Figure 6: the residuals driven from the GJR-GARCH model……………………….……....22

Figure 7: the forecast errors from the ARIMA model………………………………………..23

Figure 8: the shape of New ICU Patients variable in 2020…………………………………...i

Figure 9: the shape of new tests variable in 2020……………………………………………ii

Figure 10: the shape of COVID variables Forecast in 2020…………………………………iii

List of tables

Table 1: the results of GJR-t-GARCH (1,1) ……………………………………………….....21

Table 2: the results of regressing the US residuals on our forecast errors.……………………..…24

Table 3: the results of regressing the US standardized residuals on our forecast errors………..24

List of abbreviations and acronyms

ACF: auto-correlation function

AIC: Akaike information criterion

AR: Autoregressive model

ARIMA: Auto Regressive Integrated Moving Average

GARCH: Generalised Auto-Regressive Conditional Heteroskedasticity

GJR-t-GARCH: Glosten, Jagannathan and Runkle model (GJR Model)

IHME: University of Washington's Institute for Health Metrics and Evaluation

iid: Independent and identically distributed

LM: Lagrange Multiplier test

MA: Moving Average model

OLS: Ordinary least squares

OxCGRT: Oxford Covid-19 Government Response Tracker

PACF: partial auto-correlation function

TGARCH: Threshold GARCH Model

US: United State

Acknowledgements

I would like to thank my teacher and research director Professor Simon van Norden for his guidance and unwavering support. I feel incredibly fortunate to have had the opportunity to learn from him and express my deepest gratitude for everything he has done for me

1. Introduction

In February 2020, financial markets were disrupted and stock markets across the world suddenly began to crash in reaction to instability due to the pandemic.

Because of the volatility of the market for some dates, the change in the stock is impressive. As an example of this, “the Dow and S&P 500 have both been seeing drops due to uncertainty around the global coronavirus pandemic, while the Chicago Board of Exchange Volatility Index has been rising steadily since the middle of February as the virus began to spread around the world”[1]. The Dow Jones Industrial Average (DJIA) index dropped by around 8,000 points in the four weeks from February 12 to March 11, 2020, which was “neither a harmless event”[2].

New record lows in the yield on 10-year and 30-year US Treasury securities with the 30-year securities falling below 1% for the first time in history showed the realization that Covid-19 could greatly impact all aspects of life. The health and economic costs of the pandemic have been severe in numerous countries[3].

In the US, the S&P 500 fell 8.4% in February 2020, then plunged 12.5% in March as the pandemic essentially paralyzed the global economy according to USA Today on April 2020[4].

Below we see the variations of S&P 500 returns in 2020.

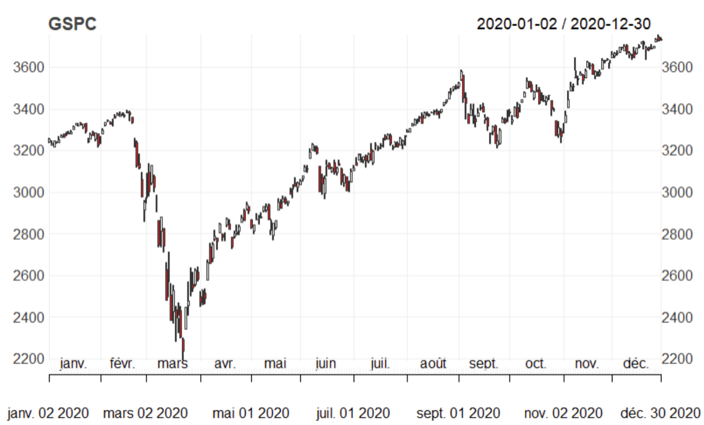


Figure (1) shows the S&P 500 returns in 2020 during the first year of COVID-19.

[1] https://graphics.reuters.com/USA-MARKETS/0100B5L144C/index.html
[2] https://www.statista.com/statistics/1104278/weekly-performance-of-djia-index/
[3] https://www2.deloitte.com/xe/en/insights/economy/emerging-market-economies-coronavirus-pandemic.html
[4] https://www.usatoday.com/story/opinion/2020/04/01/coronavirus-economic-crisis-calls-for-global-solution-column/5090913002/

Figure (1) shows the S&P 500 dropping 34% from its high on February 19, 2020, to its low in March. According to Forbes, these numbers were "not seen since the Great Depression."

This has attracted the attention of researchers around the words as they try to understand the initial effect of COVID-19 on the financial market and investigate the new era after Covid-19.

Alain et al. (2020) and Acharya et al. (2020) both focused on market volatility and found that COVID-19 played a big role in market variations in the early stage of the COVID shock by increasing the market volatility, although they used different measurement tools and approaches to examine the change in the equity market. Basuony et al. (2021) collected the details of research done in 2020. Their focus was on the volatility of the equity market as well and by using the eGARCH model, they found an "unprecedented" increase in conditional volatility and the bad state probability across all the markets. Alfaro et al. (2020) show that unexpected changes in the trajectory of COVID-19 infection predicted US stock returns between January and April 2020.

The papers above gave us an overview of the effect of COVID-19 on the financial market and its role in market volatility.

This research aims to explore the impact of COVID-19 on the US financial market throughout the entire first year, encompassing the market collapse and subsequent rebound, in addition to addressing the influence of two COVID waves, with the second wave being notably larger than the first. These elements are crucial to obtaining comprehensive and nuanced findings. By adopting a novel approach and focusing on measures of COVID "news" rather than relying solely on individual variables, we recognize that markets are driven by information and news. This approach allows for a more accurate understanding of the market's response to the pandemic.

Furthermore, by using the GJR-t-GARCH model, our analysis considers the complex interplay of leverage effects and non-normality, factors that can significantly influence market behaviour during turbulent times like those experienced during the COVID-19 pandemic.

By combining these tools and considering the market dynamics, leverage, and non-normality, this study unveils deeper insights into how COVID-19 had a far-reaching impact on the US financial market, affecting both returns and volatility patterns.

The research is organized as follows:

In Chapter 2, we survey the literature regarding volatility in the equity market during the pandemic.

In Chapter 3, we discuss the data sources and definitions.

In Chapter 4, we define the methodology details regarding,

- the ARIMA model to forecast COVID data and construct the news variables.
- GJR-t-GARCH model.
- LM-style testing for omitted variables.

In Chapter 5, we present results with robust standard error; in Chapter 6, we have our conclusion.

2. The era of COVID and uncertainty

As of the end of December 2020, there were already more than 80 million confirmed cases of COVID around the world. Numerous authors studied the impact of COVID on the market in different countries. Some papers also paid special attention to some days with high changes in the stock market during the early stage of COVID starting in February 2020. The days with a big amount of COVID News were the center of interest to find any links between the movement of stock returns and COVID news in those days. The effect of the surprise in the stock market is another factor that attracted researchers to answer the question of whether the surprise in the stock market happens locally or globally.

Different COVID series and transformations were investigated to capture significant results.

2.1 Proxy variables

To investigate the link between the COVID crisis and the change in the financial market, we need to have an efficient proxy for the COVID pandemic to show its impact on the financial market. Most research navigated around the confirmed cases, the number of new deaths or other variables which can be selected as a measurable proxy.

To answer the question about the relationship between national stock prices and economic activity during the early stage of the pandemic, **Steven J. Davis, Dingqian Liu, and Xuguang Simon Sheng** (2021) used workplace mobility as a proxy of economic activity and use regression to their panel of 35 countries s from 17 February to 21 May 2020. They show that the global and US stock market crashes, in reaction to the pandemic, are “many times larger than implied by a standard asset-pricing model”. This could be a piece of plausible evidence for the magnitude of the COVID-19 output disaster in the early stages of the COVID-19 pandemic.
Basuony et al (2021) collected daily data for the confirmed, deaths, and recovery cases. They showed that COVID-19 had an adverse impact on returns. Saying that they found an “unprecedented” increase in conditional volatility and the bad state probability across all the markets during the pandemic.

Besides investigating the reactions at the aggregate or market level, **Alfaro, Chair, Greenland, and Schott (2020)** used data on the cumulative number of COVID-19 cases s from January 22 through April 10, 2020. To examine the relationship between unanticipated changes and returns at the firm level OLS regressions were used in their research. They found a counterclockwise[5] relationship between US stock performance and real-time changes in COVID-19 infection projections.

2.2 Expectations and their influence on the Volatility in the Market

Most of the early research put the accent on the early stage of COVID-19 and its volatility. The authors highlight the cause of the incident in the United States, China, Japan, Italy, France, and other countries in which the financial market got hit by the pandemic, although the impact was not symmetric in all markets.

Alan, Engle and Karagozoglu (2020) focused on stock market volatility measures based on GARCH models and found that the number of active COVID-19 cases and the curvature of the active-case trajectory help predict stock market volatilities in a cross-section of countries. Their results show that the daily number of active cases and the curvature[6] are significant predictors of a daily cross-section of both realized volatility and the GJR-GARCH volatility in global equity markets over the period of January 22nd to May 1st of 2020. They also found that higher OxCGRT[7] Stringency Index levels result in lower stock market volatilities. Although the Stringency index is not considered a direct proxy of Covid, it is intended to measure how intensively governments react to Covid (as we discuss below.)

Acharya et al. (2021) studied the effect of COVID-19 containment measures on expected stock price volatility in some advanced economies including the US, Italy, Germany, and the eurozone

[5]Counterclockwise relationship is considered as an opposite or negative relationship between two variables. It describes the relationship between variables that exhibit an inverse correlation.
[6] Curvature refers to the degree of deviation exhibited by a plotted curve or data points. It is a measure of how the shape of the curve varies from linear. The rate of change of the slope at a given point is expressed by the second derivative which is defined as curvature and is used in analyzing and identifying patterns, trends, or changes in the data.
[7] https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker

from January 3, 2020, to October 22, 2020, including the initial tightening, easing, and retightening stages.

They used event studies with hand-collected minute-level data and panel regressions with daily data. To complete the event study, the model used to construct the counterfactual volatility is an ARIMA (1,1,1) model augmented with two additional predictors: the stock price index itself, and the GARCH-implied volatility. The ARIMA component captures the persistence of historical patterns of volatility, while the stock price and the GARCH components capture new information associated with the announcement.

Their results suggest the “existence of an intertemporal trade-off”: In the early stage of COVID, stringent containment measures may cause short-term economic disruptions, but they may reduce medium-term uncertainty by boosting markets’ confidence that the outbreak would be under control more quickly. Their results showed COVID containment measures reduce six-month-ahead expected stock price volatility indices.

3. Data

In this section, we will describe the data to be used in our models.

Regarding the data on the S&P 500 index, we use quantmod[8] available package in R. The observed sample window starts form January 1st to December 31st, 2020. This will help to detect all the patterns of the COVID-19 throughout the whole year as we aim to examine its effect on the S&P 500 index. We gathered daily data regarding COVID-19 from the OxCGRT database. The Oxford Covid-19 Government Response Tracker (OxCGRT) is a project that gathered data on COVID-19 policy measures for the years 2020, 2021, and 2022. This dataset was continuously updated in real-time to analyze the diversity in government responses and assess the impact of various policies on the COVID-19 pandemic and other relevant outcomes. We selected the most relevant variables related to COVID-19 in our dataset: "new cases", "new deaths", "positivity rate", and "stringency index". The chosen timeframe covers the entirety of 2020, thereby considering both waves of COVID-19.

[8] Quantitative Financial Modelling & Trading Framework for R. The quantmod package for R is designed to help building, testing, and deploying statistical trading models.

4. Methodology

In this section, we describe the approaches used to handle the data as well as the models to compute our results.

4.1 Modeling S&P 500 daily returns during COVID

GARCH models

As stock market returns show periods with very high or very low volatility~~,~~ GARCH models or Generalised Auto-Regressive Conditional Heteroskedasticity models, help us to capture the changes in volatility which were especially important during the pandemic. To explain the GARCH model, we start first with the return equation.

1. $r_t = \mu + \epsilon_t$

Where rt is the return at time t which contains the expected return μ and the error term εt.

The epsilon or error term is equal to

2. $\epsilon_t = \sigma_t z_t$

The sigma σ_t in the equation represents the volatility of z_t and $z_t$is a standard Gaussian variable, i,i,d and normally distributed N(0,1).

GJR-GARCH model

The Glosten, Jagannathan and Runkle model (GJR Model) generalized the simple GARCH model to allow for negative and positive shocks to have unequal effects on volatility. This property is commonly called the leverage effect. For modelling the US returns variations caused by the

COVID shocks, we applied the GJR-GARCH model, which is also known as the threshold GARCH or TGARCH model.

Here, we have a GJR-GARCH (p, q) for the variance equation:

3. $\sigma_t{}^2 = \omega + \sum_{i=1}^{p}(\alpha_i + \gamma_i I_{t-i})\epsilon^2{}_{t-i} + \sum_{j=1}^{q}\beta_j\sigma^2{}_{t-j}$

In which, $\omega > 0$. The α is equal to or higher than zero. The β is equal to or higher than zero. p and q determine the number of lags used in the model.

The volatility dynamics in GRJ-GARCH (1,1) model are given by:

4. $\sigma_t{}^2 = \omega + (\alpha + \gamma I_{t-1})\epsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1}$.

$$I_{t-1} = \begin{cases} 1, & r_{t-1} < \mu \\ 0, & r_{t-1} \geq \mu \end{cases}$$

GARCH.X

In the early period of our research, we tried to capture the impact of the Covid shock on US returns by adding an external regressor to our GJR-GARCH model.
The equation is represented below:

5.

$$\sigma_t{}^2 = \omega + \sum_{i=1}^{p}\alpha_i\epsilon^2{}_{t-i} + \sum_{j=1}^{q}\beta_j\sigma^2{}_{t-j} + \sum_{k=1}^{r}\gamma_k\, I_{\{\epsilon_{t-k}<0\}}\epsilon^2{}_{t-k}) + \sum_{l=1}^{s}\lambda_l x_{l,t-1}$$

As the model showed some issues with the external regressor, to handle the data, we took another approach, LM style testing, to check the relationship between the variation of US return and the Covid shock.

To complete the test, we run a simple GARCH model on US returns, and we saved two series:

- $\boldsymbol{u_t}$: the residuals from the mean equation.
- $\boldsymbol{h_t}$: the estimated variance from the variance equation.

4.2 COVID News and ARIMA models

As the financial markets move in response to the news, we tried to measure the news to calibrate the movement of US returns in reaction to COVID shocks. The news can be measured by the difference between forecasts and actual outcomes which is known as the forecast errors. To forecast the data, we used ARIMA models to create forecasts of COVID variables and then, we subtracted them from the actual COVID data to create forecast errors.

ARIMA models

ARIMA models consist of two steps:

1. Differencing to make the time series stationary.
2. Using lagged observations in a time series to predict the future behaviour of a time series. This step contains a combination of two models: the Autoregressive (AR) model and the Moving Average (MA) model.

The AR model forecasts a variable using a linear combination of its previous values:

$$6.\ y_t = c + \varphi_1 y_{t-1} + \varphi_2\, y_{t-2} + \cdots + \varphi_p\, y_{t-p} + \epsilon_t$$

MA model or the moving average model is like an AR model, except it is a linear combination of previous error terms:

$$7.\ y_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_p \epsilon_{t-q}$$

ARIMA Model Parameters

The ARIMA model includes three main parameters p, q, and d.

p: The order of the autoregressive model (the number of lagged terms), described in the AR equation.

q: The order of the moving average model (the number of lagged terms), described in the MA equation.
d: The number of differences required to make the time series stationary.

Seasonal ARIMA

The SARIMA model includes the p, q, and d parameters, but also an extra set of parameters to take care of time series seasonality. This parameter set P, Q, D, and additional parameter m.
m: The seasonality of the model. In our time series, the seasonality of a time series repeats weekly, then m = 7.
P: The order of the seasonal AR model.
Q: The order of the seasonal MA model.
D: The number of seasonal differences applied to the time series.

We used auto.arima to get the best p, d, and q values. As auto.arima ignores seasonality, we checked which combination of seasonal order between (1,1,1), (0,1,0) and (0,1,5) minimizes the AIC.

ACF test and PACF test are also used to give us insight regarding the number of lagged terms.

4.3 Measurement of model performance

To select our ARIMA model, we used the (AIC), the Akaike information criterion.

The equation for the AIC is described as follows:

8. $AIC = 2K - 2\ln(L)$

K is the number of independent variables used and **L** is the log-likelihood estimate (a.k.a. the likelihood that the model could have produced the observed y-values

4.4 The expanding window estimation of the ARIMA models

By using the expanding window or rolling windows estimation, we can be sure to predict the next time step using only data that would have been available to us at the time to avoid using the future to analyze the past.

Rolling forecasts with expanding windows

Rolling forecast with an expanding window of a time series model evaluates the stability of the model over time. The model is running in an expanding window meaning that it’s run each time with a size on one more day (t+1).

In our model, while rolling forecast, we kept the coefficients constant. Our expanding windows have a fixed start point (fixed lower bound) and then the upper bound of the window is rolled forward. In other words, the window gets bigger and bigger each time the model is rolled over the data. The size of the rolling window is the size of the data sample and each time, we add one observation at a time to the new estimation. We need to make clear that p, d, q, P, D, Q are also constant as we expand the window. And the phi's and theta’s from equations 6 & 7 are kept constant as we expand the window.

The new estimates are used to generate forecasts (and forecast errors) up to 7 days (one week ahead) at each point in time.

4.5 LM Tests for Additional Variables

Lagrange Multiplier (LM) tests allow us to test whether adding a variable to a model will improve its fit without having to estimate the new model. Given the complexity of estimating GARCH-X models and the large number of potential explanatory variables to test, we used this approach, at first, to evaluate candidate COVID variables. In the case of a GARCH model, a *necessary* condition for a COVID variable *X* to improve the fit of the mean equation is that the residuals u(t) from the mean equation be correlated with *X*. Similarly, a *necessary* condition for a COVID variable *X* to improve the fit of the variance equation is that the standardized squared residuals $u^2(t)/h(t)$ be correlated with *X*.

Therefore, we regress the residuals u(t) on the forecast errors of each COVID variable in our panel. We then repeat the regression using squared residuals divided by h(t) in place of u(t), the standardized residuals to verify whether *X* could improve the fit of the variance equation.

In our analysis, to explore additional evidence to determine the potential significance of the COVID variables in the variations of US returns, we also employ LM-style testing as an alternative approach to assess the relationship between changes in COVID variables and variations in US returns. This method allows us to further examine[9] the possible impact of COVID-related factors on the S&P 500 and gain deeper insights into their influence on returns fluctuations.

[9] Independently of GARCH models

5. Results and analysis

In this section, we examine the correlation between the COVID variables and the US returns. First, we examine the variables' shape.

5.1 Variables

Figure 2 shows the variations in the S&P 500 index return in 2020 the first year of the pandemic. The market suffered a string of increasingly negative returns in February before a period of extreme volatility in March and further bursts of volatility in June and the autumn.

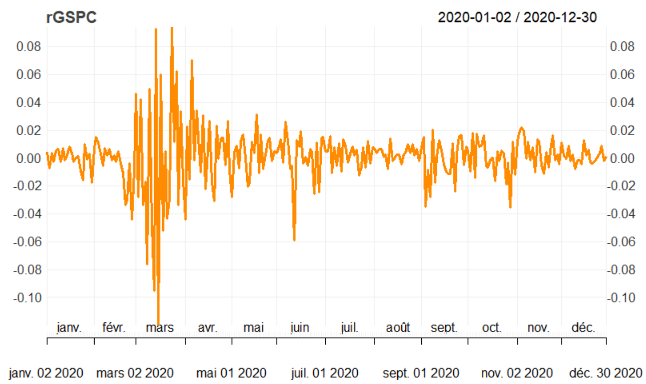


Figure (2) shows the US index returns during the first year of the pandemic.

From our COVID data panel, we selected four series as explanatory variables: the number of new cases, the number of new deaths, the positivity rate of COVID tests, and the stringency index. The latter captures the government's reactions[10] to the COVID pandemic, and its inclusion allows for the possibility that the pandemic's impact on businesses might depend not only on the future spread of the disease but also, on how government policies react to the disease's spread.

[10] The government reactions include closing businesses, lockdowns etc.

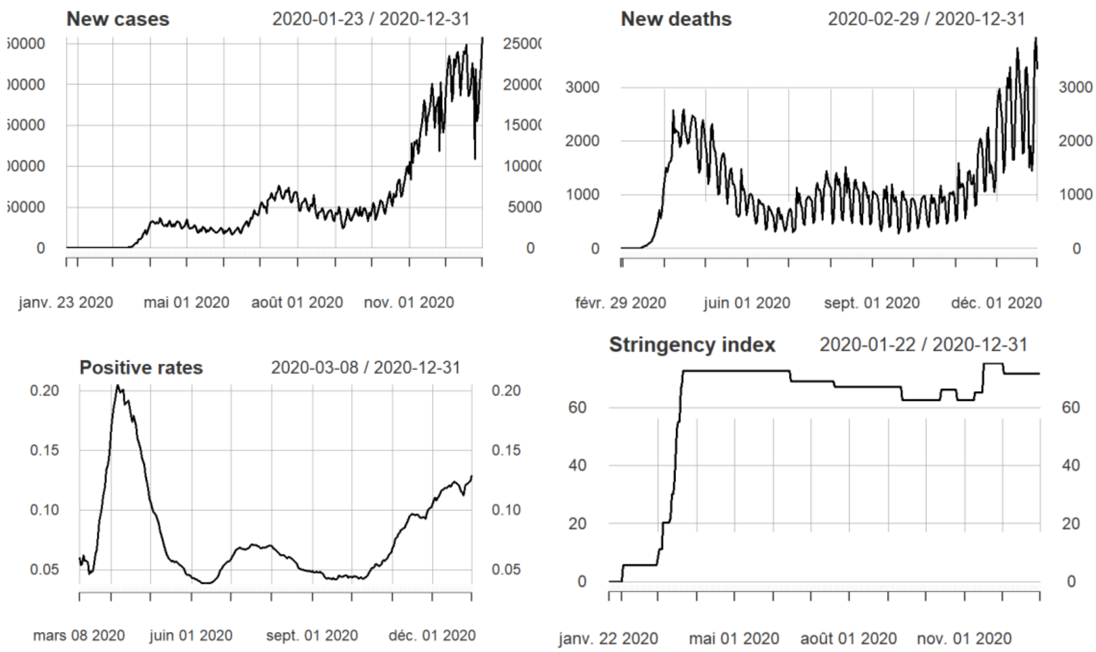


Figure (3) shows the variation of our selected COVID variables, the new chases, the new deaths, the positivity rate, and the stringency index in 2020.

As we can see above, in Figure (3), the number of new cases in early 2020 is near zero, then climbs in two phases before skyrocketing at the end of the year. A weekly reporting effect distinguishes the number of deaths, giving it the zigzag shape. Unlike the number of new cases, its surge at the end of the year is not much larger than that of the February-March period. On the other hand, the positive test rates peaked sharply at the beginning of 2020, with a smaller and more gradual surge at the end of the year. This reflects the fact that in early 2020, testing was restricted to those most likely to be ill. As testing becomes more widespread after May, the positive rate decreases. And finally, as the disease expands to more and more states, the positive rates increase as well.

The stringency index, which is calculated as the mean score of nine metrics[11], each taking a value between 0 and 100[12], has a more discrete shape. As shown in the graph, the stringency index

[11] "The nine metrics used to calculate the Stringency Index are school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls". (*Mathieu Edouard at all. 2020).*
https://ourworldindata.org/covid-stringency-index
[12] A higher score indicates a stricter response (i.e., 100 = strictest response).

increases starting in March reaches its quasi-maximum in early April and remains roughly stable while recording its absolute maximum in early November.

5.2 Rolling forecasts

We think that market returns should reflect changes in the expectations of market participants, or "news". To estimate these expectations and their changes, we use Seasonal ARIMA models to first create forecasts for our four explanatory series. These are rolling forecasts, based on expanding window estimation. Changes in these forecasts are then used as our proxy of news about the characteristics of the COVID pandemic.

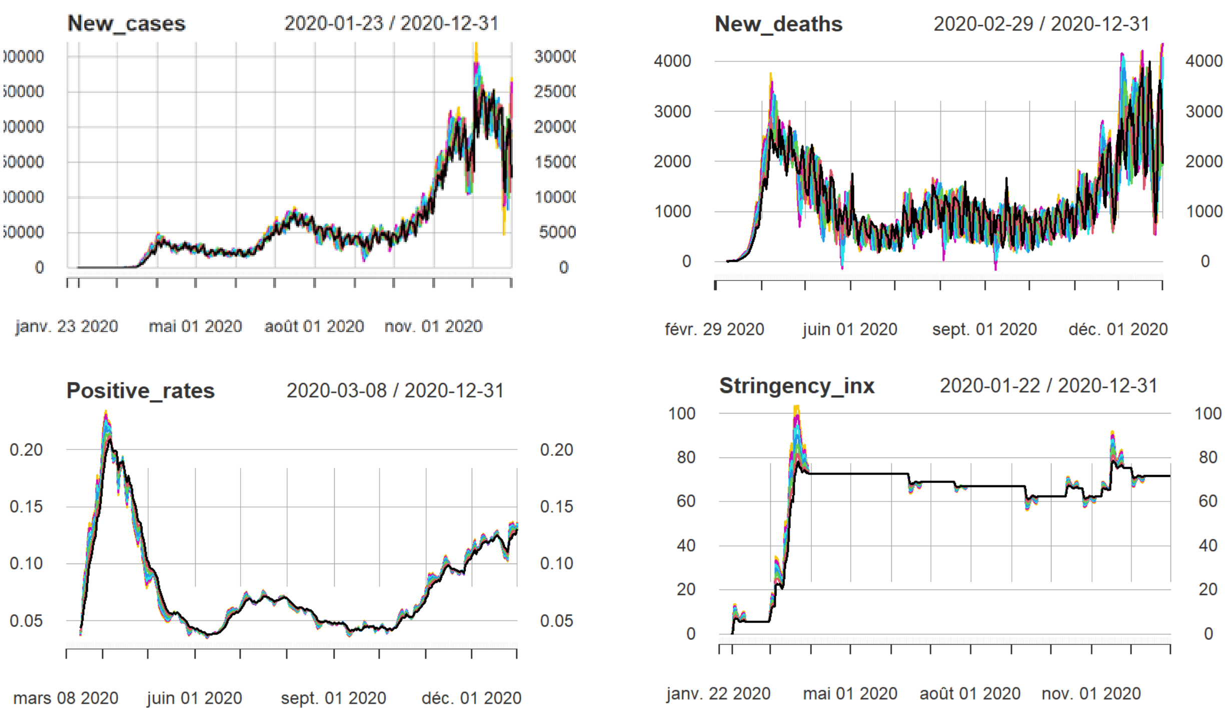


Figure (4) shows the rolling 7-day ahead forecasts for time t of our four selected variables.

The black line represents the actual data, and the coloured lines represent the forecasts. A closer look may be seen in Figure (5) which frame only the last week of the stringency index and the positive rates in 2020. We can clearly see that the red colour shows the forecast for day t+1 and the green line represents the forecast for the day t+2. As can be seen, the last forecast day t+7 is represented with an orange colour.

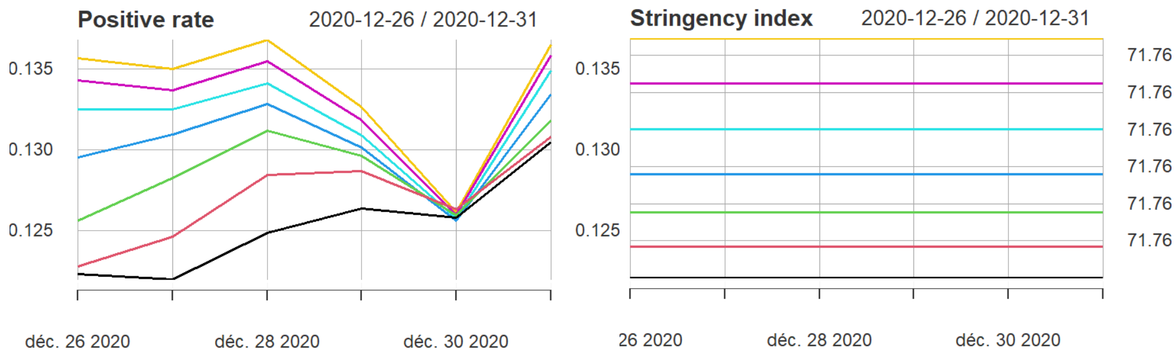


Figure (5) represents the positive rates and stringency index series including the 7 days forecasts for the last week of the year.

Regarding the fits of our forecast model shown in Figure (4), the forecast for the new cases fits well until November, when the volatility of the series increases, causing a similar increase in the volatility of the forecasts. In the forecast for the number of new deaths, we dealt with the high weekly seasonal effect and thus, we have plenty of highs and lows in our forecast and a more limited fit.

Contrary to the two precedent variables, we observe a different behaviour for the positive rates, and the stringency index. Forecasts for the positive rates largely track the data, although in an upturn (a downturn), the model overestimates (underestimates) the increasing (decreasing) patterns. In the case of the stringency index, we see some overestimation when the stringency reaches its first maximum in April, and then after a period of stability we can see again some instability re-emerge from mid-2020.

5.3 LM style testing

In the early stage of our research, we tried to capture the volatility in US returns by using GARCH models. As the first attempt, we estimated the GJR-t-GARCH-X model.

By adding the external regressors at the level and/or the variance equation, we tried to see whether the change in the model is followed by any improvements in the model's results. We tried rescaling the data and different transformations to improve the results. And finally, we tried different software packages including ugarchfit (x) from rugarch package as well as garch(x) from garchx package and found that estimates of the coefficients on our COVID variables always converged to 0.000.

To see if there was any other evidence that the COVID variables may have played an important role, we used LM style testing as an alternative way to check the correlation between the COVID variable changes and the US returns variation.

5.4 Residuals of the GJR-t-GARCH and its conditional variance

As mentioned in the methodology section, we are calculating correlations, which are necessary for the LM test to conclude that adding a variable from our panel will improve the model's fit.

During the pandemic, the financial markets experienced high volatilities and we, first estimated that the GJR-t-GARCH model can handle better the variations in the US returns and the asymmetry between negative and positive shocks caused by the pandemic. To choose the best GARCH model, we run different models on our US return series. Akaike Information Criterion (AIC) for the eGARCH with normal distribution and with t-distribution are respectively **-5.6104** and **-5.6749**. The AIC for the GJR -t-GARCH model and GJR-GARCH with skewed-Generalized Error Distribution are respectively **-5.7179** and **-5.7301**. By comparing the AIC of different GARCH models on US returns, we chose the GJR-t-GARCH model for our US series.

The US returns residuals or the conditional variance is driven from the GJR-t-GARCH model to complete the LM test.

Below, we have the results of the GJR-t-GARCH model on US returns:

```
Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.001883    0.000663  2.84006 0.004511
ar1    -0.538107    0.085782 -6.27299 0.000000
ma1     0.353566    0.100476  3.51891 0.000433
omega   0.000009    0.000023  0.39436 0.693317
alpha1  0.169751    0.203548  0.83396 0.404303
beta1   0.725212    0.232314  3.12169 0.001798
gamma1  0.208073    0.358572  0.58028 0.561724
shape   4.633235    4.164637  1.11252 0.265915
```

Table (1) shows the results of GJR-t-GARCH (1,1).

As seen in equations (6) and (7) in the methodology part, AR1 is the coefficient estimate of y_{t-1}which is represented as phi1 φ_1 in the formula. In our GARCH model, y_{t-1} is r_{t-1}, the return of the day before. ma1 is the coefficient estimate of ϵ_{t-1}which is represented as theta θ_1 in the formula.

In the result, φ1 is denoted by ar1 which is **-0.5381** and is very significant, implying that there is some amount of negative autocorrelation. θ1 is denoted by ma1 which is **0.3535** and very significant. The estimated mean μ is near 0, and ω, omega is also 0 but not significant.

Alpha1, **0.1697** is not significant but β1, **0.7252** is highly significant which implies persistent volatility clustering. We need to mention that the large value of β causes σ_t to be highly correlated with σ_{t-1} and gives the conditional standard deviation process a relatively long-term persistence (D.Ruppert & Matersson, 2015). Gama1, γ_1, represents the asymmetric adjustment to past shocks and is not significantly different from 0, implying that there is no significant evidence of the leverage effect in our sample. Regarding the value of the shape parameter, **4.63**[13], considered low for the shape parameter, shows that the US returns series has quite fat tails, which is normally observed in financial time series.

The residuals of the GJR-t-GARCH model are as below:

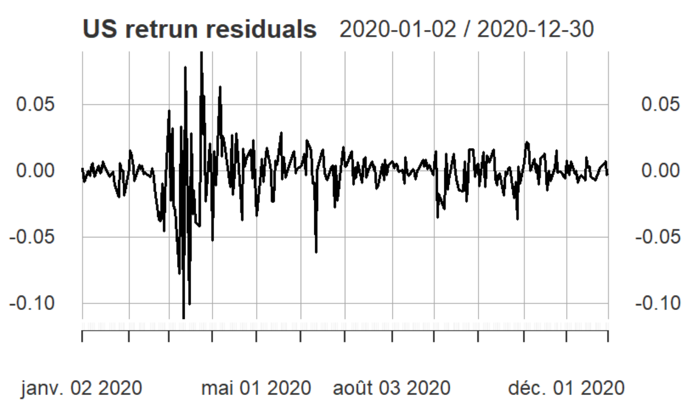


Figure (6) shows the residuals driven from the GJR-t-GARCH model.

[13] The lower value of shape implies the fatter tails of the distribution (normality implies that shape is equal to infinity.

Below, we have the shape of forecast errors of selected COVID variables, the new cases, the new deaths, the positive rates, and the stringency index. As shown in the graphs, we have large GARCH residuals in early 2020 which is like the shape of the forecast errors in the positive rates and the stringency index. The pattern is different for the forecast errors of other variables, new cases, and the new deaths.

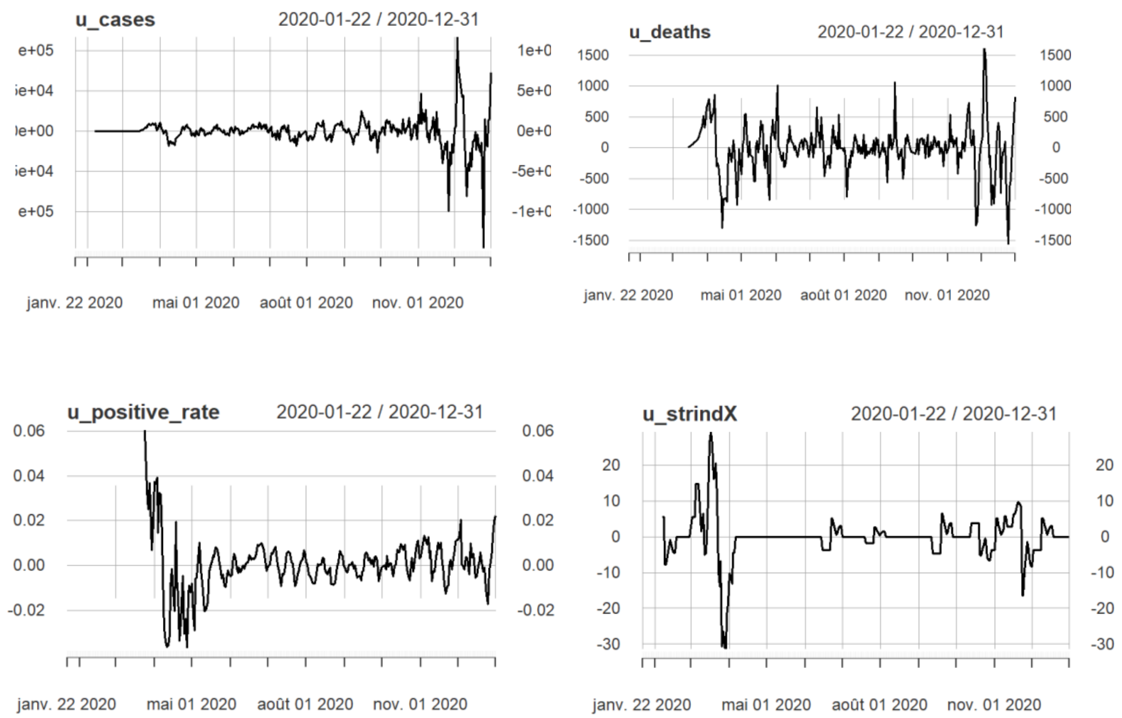


Figure (7) shows the forecast errors from the ARIMA model.

5.5 Regressing the US residuals on forecast errors

In the next tables, we report the results of our regressions. We collected coefficient estimates, standard errors, and p-values for the selected COVID variable's forecast errors.

As can be seen in Table 2, below, only the coefficient estimates of positivity rates **0.2839808** and the stringency index **-0.0006843** are significant with the p-value of **0.00308 **, and 0.00262 **** respectively. Both coefficients are statistically significant and in addition, the stringency index is also economically significant[14].

[14] When the stringency index forecast error goes from its maximum of 29.332635 to its minimum of -31.219947, the daily return changes from its min -0.1198 to 0.0938 in 2020.

Residuals	Estimates	Std. Error	t-value	p-value	R-squared	Adj. R-squared
New cases	2.614e-08	9.017e-08	0.29	0.772	0.0003734	-0.004069
New deaths	2.430e-06	3.228e-06	0.753	0.452	0.002826	-0.00216
Positivity rate	0.2839808	0.0947400	2.997	0.00308 **	0.04426	0.03934
Stringency index	-0.0006843	0.0002248	3.043	0.00262 **	0.03954	0.03527

Table 2 shows the results of regressing the US residuals on our forecast errors.

5.6 Regressing the standardized residuals on forecast errors

As can be seen in the table 3 below, our coefficients estimates are not significant.

Standardized residuals	Coeff. Estimates	Std. Error	t-value	p-value	R-squared	Adj. R-squared
New cases	1.495e-07	9.688e-06	0.015	0.988	1.059e-06	-0.004443
New deaths	-0.0001246	0.0004007	-0.311	0.756	0.0004832	-0.004514
Positive rate	0.9451	13.7170	0.069	0.945	2.447e-05	-0.00513
Stringency in	-0.005155	0.024641	-0.209	0.834	0.0001945	-0.004249

Table 3 shows the results of the regressing the US standardized residuals on our forecast errors.

6. Conclusion

Using the ARIMA model on the COVID series to construct forecast errors, “news effect” and LM-style tests, we show that although in early 2020, COVID played a huge role in the volatility of the S&P 500 index, this pattern is not consistent for the whole year in question. Our robust results provide some insight regarding the relationship between the volatility in the S&P 500 index and the positivity rate as well as the stringency index. The positivity-rate-related news may result in increased volatility but in the period of study, our sample does not show any stable relations between COVID and the change in S&P 500, suggesting that although in the early stage, COVID shock created some pressure on the market, the resilience created through time, reversed its impact. Future studies can explore further the channel through which the use of a more accurate model could provide us with a fine-tuned result. One could analyze the Covid related news and the responses of the financial market by using forecasts of the pandemic's trajectory that were offered by different organizations such as Washington University[15].

[15] At the beginning of the COVID-19 pandemic, the University of Washington's Institute for Health Metrics and Evaluation (IHME) created data models to predict and provide projections regarding the number of coronavirus cases, hospitalizations, and deaths.
https://covid19.healthdata.org/global?view=cumulative-deaths&tab=trend
https://www.healthdata.org/covid

Bibliography

Acharya, Viral V., Yang Liu ans Yunghui Zhao (2022). “COVID-19 Containment Measures and Expected Stock Volatility: High-Frequency Evidence from Selected Advanced Economies”, *IMF Working Paper No. 2021/157*, p.43. Recupéré de https://ssrn.com/abstract=4026335

Alan, Nazli Sila, Robert F. Engle and Ahmet K. Karagozoglu (2020). “Multi-regime Forecasting Model for the Impact of COVID-19 Pandemic on Volatility in Global Equity Markets”, *Volatility and Risk Institute Working Paper Stern School of Business New York University*. Récupéré de Multi-regime Forecasting Model for the Impact of COVID-19 Pandemic on Volatility in Global Equity Markets (nyu.edu)

Alfaro, Laura, Anusha Chari, Andrew N. Greenland and Peter K. Schott (2020). “AGGREGATE AND FIRM-LEVEL STOCK RETURNS DURING PANDEMICS, IN REAL TIME”, *NATIONAL BUREAU OF ECONOMIC RESEARCH*, Working Paper no 26950, Cambridge, MA. Récupéré de http://www.nber.org/papers/w26950

Basuony, Mohamed, Mohammed Bouaddi, Heba Ali and Rehab EmadEldeen (2021). “The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics”, *Journal of Public Affairs*, vol. 22. Récupéré de https://doi.org/10.1002/pa.2761

Brende, Børge (2020). “Great Recession showed countries can’t fight the coronavirus economic crisis alone”, *USATODAY OPINION*. Récupéré de Coronavirus economic crisis: Great Recession showed global fix is key (usatoday.com)

Edouard, Mathieu, Hannah Ritchie, Lucas Rodés-Guirao, Cameron Appel, Charlie Giattino, Joe Hasell, Bobbie Macdonald, Saloni Dattani, Diana Beltekian, Esteban Ortiz-Ospina and Max Roser (2020), “Coronavirus Pandemic (COVID-19)”. Published online at OurWorldInData.org. Récupéré de https://ourworldindata.org/coronavirus

Funakoshi, Minami, and Travis Hartman (2020). “March madness”, *REUTERS GRAPHICS*. Récupéré de https://www.reuters.com/graphics/USA-MARKETS/0100B5L144C/index.html

Ruppert, David, and David S. Matterson (2015). “Statistics and Data Analysis for Financial Engineering”, Second edition, New York, Springer, p. 719

Steven, J. Davis, Dingqian Liu and Xuguang Simon Sheng (2021). “SERIES STOCK PRICES AND ECONOMIC ACTIVITY IN THE TIME OF CORONAVIRUS”, *NATIONAL BUREAU OF ECONOMIC RESEARCH*, Working no Paper 28320, Cambridge, MA. Récupéré de http://www.nber.org/papers/w28320

Sucarrat, Genaro (2021). “garchx: Flexible and Robust GARCH-X Modeling”, *The R journal,* vol. 13, p.276-291

Wolf, Michael (2020). “Emerging Markets Outlook: Present tense, future tense”, *Deloitte insights.* Récupéré de https://www2.deloitte.com/xe/en/insights/economy/emerging-market-economies-coronavirus-pandemic.html

Appendix

Figure (8). shows the shape of New ICU Patients variable in 2020

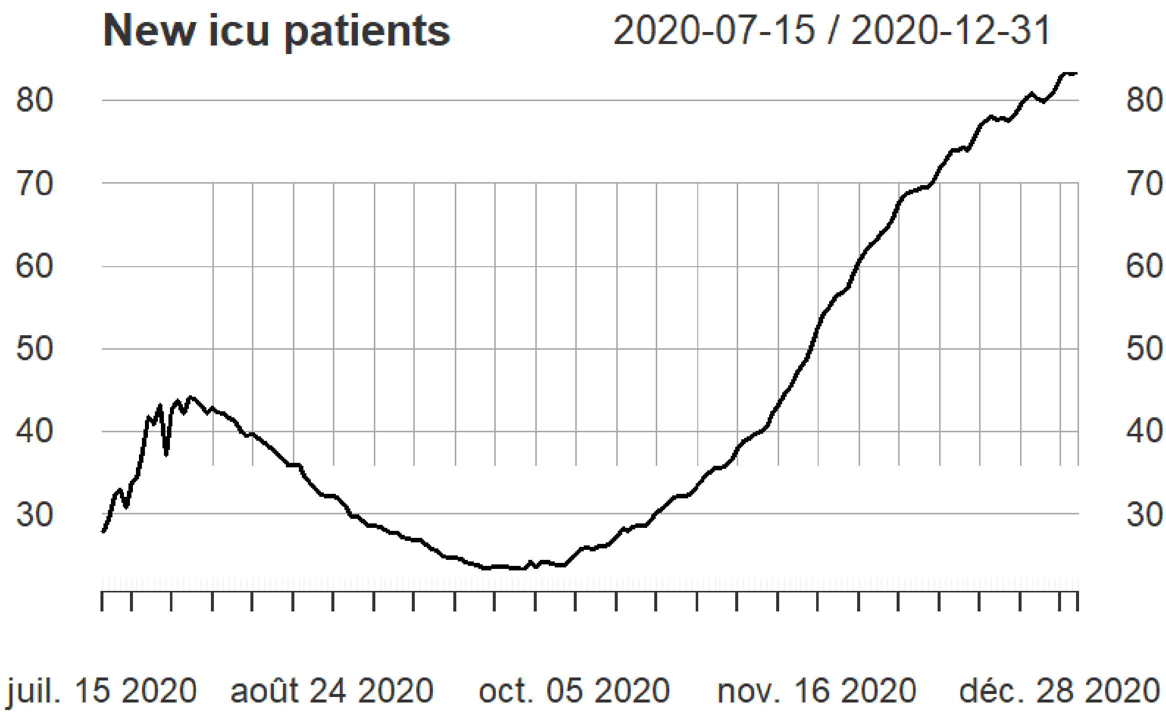


Figure (9) shows the. shape of new tests variable in 2020

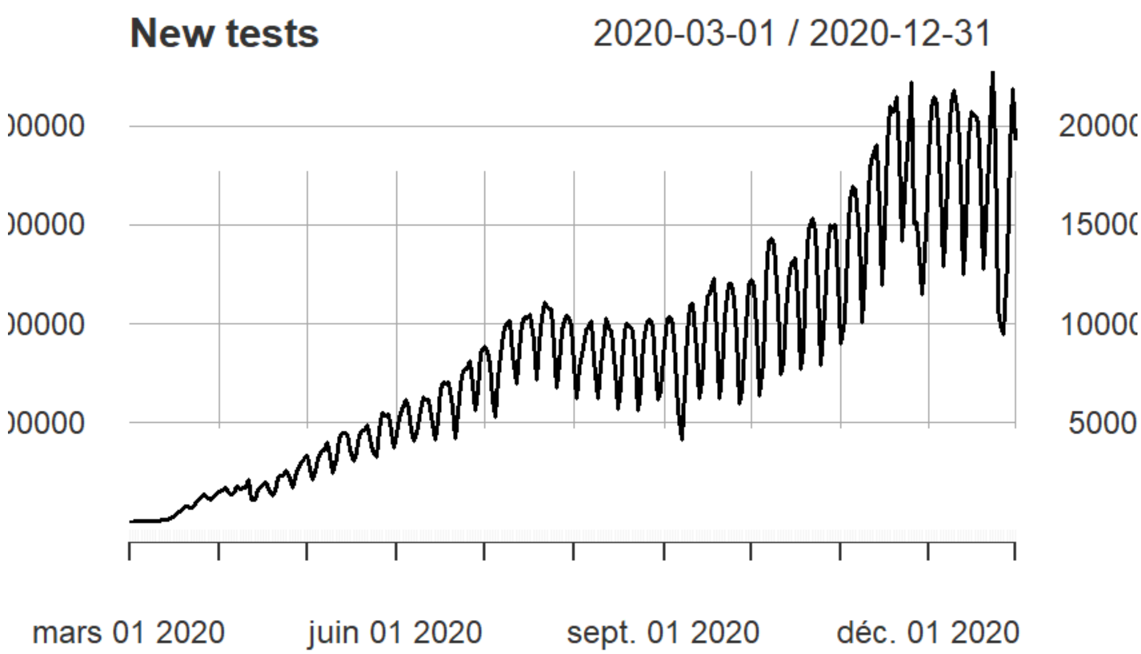


Figure (10). shows the shape of COVID variables Forecast in 2020