Oil Price Volatility Models during Coronavirus Crisis: Testing with Appropriate Models Using Further Univariate GARCH and Monte Carlo Simulation Models

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ABSTRACT

Coronavirus (2019-nCoV) not only has an effect on human health but also on economic variables in countries around the world. Coronavirus has an effect on the price of black gold and on its volatility. The shock on all markets is already very strong. Volatility patterns in Brent crude oil simulation are examined during COVID-19 crisis that significantly affected the oil market volatility. The selected crisis of coronavirus arose due to different triggers having diverse implications for oil returns volatility. Our findings indicate that model choice with data modeling is the same appropriate model EGARCH(0,2) with different parameters between pre-coronavirus and post-coronavirus. We find that oil prices are the most strongly and negatively influenced by the Coronavirus crisis. The downward movement post-covid-19 crisis is very noticeable in energy volatility. The return series, on the other hand, do not appear smooth, they rather appear volatile. We conduct a Monte Carlo simulation exercise during coronavirus crisis to investigate whether this decline is real or an artefact of the oil market. Our findings support the fact that the decline in oil prices volatility is an artefact of the covid-19 crisis.

Keywords: Oil Returns Conditional Volatility, Coronavirus Crisis, Univariate GARCH Models, Mean Equation, Variance Equation, Monte Carlo Simulation
JEL Classifications: Q43, E44, C1, I15, C15

1. INTRODUCTION

The concept of volatility is a fundamental element in understanding the financial markets, particularly in terms of risk management. After Engle (1982) and Bollerslev (1986), the econometric literature has seen the emergence of conditional heteroscedasticity models, all from the famous GARCH models and their extensions, whose applications in finance have been very successful on data high frequency (daily, weekly, etc.).

The demand for oil is relatively inelastic, so increases or decreases in the global quantity demanded are mainly determined by changes in world income. Hamilton (2009) argues that the historical price

shocks were mainly caused by major disruptions in crude oil production which were caused by largely exogenous geopolitical events such as the Iranian revolution in the fall of 1978, the invasion of Iran by Iraq September 1980 and Iraq's invasion of Kuwait in August 1990. Between 1973 and 2007, these three major events led to the disruption of the flow of oil from the main world producers which increased the oil price.

From 2005 to 2007, the drop in Saudi production was a determining factor in the stagnation of world oil production. Saudi Arabia, the world's largest oil exporter for many years. Thus, the volatility of oil production is not due to exhaustion but to a deliberate Saudi strategy of adjusting production in order to stabilize prices. On

the other hand, global demand has grown steadily. In developed countries, demand for oil follows revenue growth by around 3%. In developing countries like India and China, where incomes are growing much faster, demand for oil has grown much faster, by around 10%. Even though China consumed more oil, some other countries such as the United States and Japan consumed less. In 2006-2007, the drop in consumption in some countries can be attributed to an increase in prices, as is the case in OECD countries. Considering that the income elasticity of demand for oil in countries like the United States is around 0.5, while in newly industrialized countries it can be greater than unity, it is plausible d '' attribute the 6% increase in oil consumption between 2003 and 2005 to the demand curve caused by the increase in world GDP.

Michael Masters, manager of a private financial fund, who has been invited to testify before the United States Senate, argues that investors who bought oil not as a commodity to use but rather as an asset financial are responsible for the soaring oil prices of 2007-2008. He argues that this *financialization* of raw materials introduced a speculative bubble in the oil price (Bhar and Malliaris, 2011).

Oil prices began to rise in the United States in early 2002 and have continued to climb from a low of $ 30 per barrel in 2002 to a high of around $ 150 in mid-2008. However, as the 2007-2009 financial crisis increased uncertainty and pushed the economy into a recession in December 2007, the Americans reduced their demand for oil and reduced oil prices. From a high price of $ 150 per barrel of oil in mid-2008, the price fell to around $ 30 at the end of 2008. Although gasoline prices were likely a key factor in the decline American automaker sales in the first half of 2008, lower revenues appear to be the main factor.

The price of oil plays a role in the world economy similar to that of gold and the euro. Indeed, since the early introduction of the euro in 1999, it has first weakened against the dollar, then strengthened with a very strong correlation with the price of oil during the period 2005-2007. Likewise, gold prices have moved in a direction similar to that of oil.

The energy markets have recently been marked by considerable price movements. In particular, during the coronavirus crisis, energy prices on international exchange platforms rose sharply and record oil prices were accompanied by significant volatility and a sudden decline. Covid-19 increases this high volatility. The virus was identified by China on January 31, 2020 following a case of pneumonia declared on December 31, 2019.

Chinese demand has fallen sharply, the world consumes around 100 million barrels of oil per day, including 14 million in China. In December, the International Energy Agency (IEA) still forecast growth of around one million barrels by 2020, half of which for China.

The spread of the coronavirus worldwide and the risks of a generalized economic crisis have plunged oil prices into a recession in recent weeks. Despite a rebound observed on February 4, a barrel of Brent (the oil quoted in London) has lost a fifth of its value since the beginning of the year, falling to around 52 dollars (Figure 1). The shock on all markets is already very strong. But everything changed with the coronavirus epidemic. The Chinese economy is said to have reduced its oil needs by around 3-4 million barrels a day. Therefore, other studies show that the rise in oil prices during this century is attributed to the increase in demand for oil caused by fluctuations in global economic activity (Aastveit et al., 2015; Monfort et al., 2019).

Following the coronavirus epidemic, the barrel of Brent reference oil - oscillates for 2 months in a wide horizontal channel between 50 and 64 dollars, to the nearest dollar. Thus, a risk of a slowdown in the global economy becomes overnight a reality that no one can deny. Sellers took the lead, driving prices down by more than 10%. So here we are on the $ 50, a critic, and "said the expert." The volatility patterns of black gold returns and / or its parameters may change.

Hamilton (2003) has studied in more detail the non-linear relationship between the price of oil and the economy, arguing that the rise in the price of oil will affect the economy while the fall in the price of oil will not necessarily affect the economy. Barsky and Kilian (2001) suggested that the "reverse causality" between macroeconomic variables and the price of oil should be taken into account. That is, the price of oil affects the economy while the fluctuation of the price of oil is also affected by global economic activity. Evidence shows that the high price of oil after the 2008 financial crisis plunged the world economy into a downturn, and the price of oil is still in a period of strong fluctuations, which is a huge obstacle to economic recovery.

This article explicitly considers the importance of the covid-19 crisis when modeling the volatility of oil returns. To do this, we applied several break points to analyze the four shock periods, as illustrated in Figure 1, by applying Monte Carlo modeling for 1000 observations.

The article is organized as follows. Section 2 discusses the link and results between oil prices and its volatility and crisis. Section 3 describes the data. Section 4 introduces our empirical framework resumed in mean equation and variance equation. 5 presents the main results of the paper. It also includes the discussion of the appropriate models of volatility and a discussion on the Monte Carlo Simulation. Some final remarks appear in section 6.

2. LITERATURE REVIEW

The main findings of the Krichene's study (2007), that studied the dynamics of oil prices during January 2, 2002-July 7, 2006, were that these dynamics were dominated by frequent jumps, causing oil markets to be constantly out of-equilibrium. While oil prices attempted to retreat following major upward jumps, there was a strong positive drift which kept pushing these prices upward. The oil prices were very sensitive to news and to small shocks. Krichene (2007) also extends his study by analyzing market expectations regarding future developments in these prices. Based on a sample of call and put option prices, he computes the implied risk neutral distribution and finds it to be right-skewed, indicating

Figure 1: Oil price evolution: Pre and post coronavirus
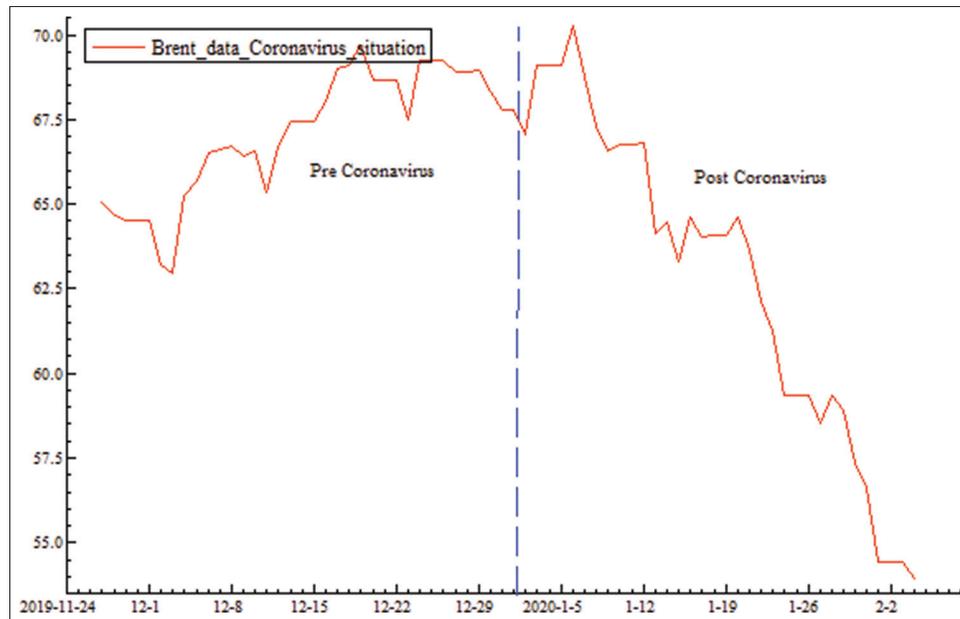
Source: Made by the author

that market participants maintained higher probabilities for prices to rise above the expected mean, given by the futures price.

The characteristics of the risk-neutral distribution, namely high volatility and high kurtosis, indicate that market participants expected prices to remain very volatile and dominated by frequent jumps. Oil prices can be correlated with the prices of other commodities such as agricultural products (wheat, corn and soybeans), energy products (natural gas, gasoline and fuel oil) and metals (gold, silver, copper and palladium) to name a few. However, all of these prices are influenced by common macroeconomic factors such as interest rates, personal income, industrial production, exchange rates and inflation. In addition, some of these products are supplements (for example, silver and copper) or substitutes in consumption (for example, gold and silver), and inputs in the production of others, (for example, petroleum, silver and copper).

Increases in commodity prices usually fuel expectations of higher inflation. If these increases cannot be explained by fundamentals alone, then monetary policy may view such increases as a signal of inflationary expectations. Assuming Central bank's target inflation, increasing Fed funds rates may follow an increase in inflationary expectations. Market participants may respond to inflationary expectations by increasing the demand for gold and therefore its price and selling the currency and thus depreciating it; or if the Central banks respond to such inflationary expectations vigorously, the opposite may occur, with the price of gold dropping and the value of the currency appreciating. Employing the price of gold as a proxy for inflation in our model allows us to explain the behavior of oil in terms of inflationary expectations.

If inflation rises, most of the commodities would be expected to rise as well, and in this case gold can serve as a satisfactory proxy. Expectations of rising inflation are generally fueled by increases

in commodity prices. If these increases cannot be explained solely by fundamentals, then monetary policy can view these increases as a signal of inflation expectations. Assuming central banks target inflation, the increase in Fed funds rates could follow an increase in inflation expectations. Market players can respond to inflationary expectations by increasing the demand for gold in order to increase its price and depreciate the currency by increasing its supply; or if the central banks respond vigorously to these inflationary expectations, the reverse may occur, the price of gold falling and the value of the currency appreciating.

Using the price of gold as an indicator of inflation in our model allows us to explain the behavior of oil in terms of inflation expectations. Oil is traded globally in US dollars. The role of the US dollar exchange rate has become very important in affecting and being affected by the price of oil. The Organization of the Petroleum Exporting Countries (OPEC) sets the price of oil in US dollars taking into account several factors such as the global fundamentals of world demand, the growth of the world economy, the strength of the US dollar measured in terms of other currencies, including the euro, Japanese yen, British pound, Swiss franc, Chinese yuan and others. OPEC then examines the appropriate global supply with the aim of setting a stable price. An important factor to take into account is that the Cartel is increasing the price of oil to compensate for the decline in the purchasing power of their dollar-denominated oil revenues.

Hammoudeh et al. (2009) found that oil and silver prices and the exchange rate can send signals to monetary authorities about the future direction of short-term interest rates as defined by the Treasury bill rate American. Rising oil and silver prices and an appreciation of the US dollar against major currencies, if they occur simultaneously, are signals of a tightening of monetary policy. However, this argument can go in the opposite direction. Indeed, if the central bank is concerned about deflationary

pressures during an economic recession when oil and gold prices are relatively low, then the central bank can follow an expansionary monetary policy and further reduce the Fed funds rate for stimulate spending and prevent deflation.

The anticipation of an economic recovery may increase the prices of oil, gold and other raw materials. This scenario describes the economic conditions in the United States during the period 2000-2002. First, the bursting of the NASDAQ bubble and the terrorist attacks of September 11, 2001 plunged the US economy into recession for most of 2001.

The Fed had remained unsure about the progress of economic recovery, so it followed an easy monetary policy and it continued to do so up until 2004. This extended period of easy monetary policy fueled the increases in housing prices and also the subsequent increases in oil, gold and other commodities. Increases in the price of gold may cause depreciation in the U.S. dollar against the major currencies as traders sell the U.S. currency and buy gold. If on the other hand, monetary policy becomes tight to fight potential inflation and the Fed increases interest rates, then traders will sell gold and buy dollars. The results of Hammoudeh et al. (2009) also show that investors and the central bank should give the price of gold a higher weight in making decisions. Thus, the monetary authority and investors should focus more on the price of gold in such a case to obtain clues on the future direction of central bank policies and the behavior of the dollar visa-vis the other major currencies. Motivated by their findings we use the price of gold in our list of important explanatory variables. Furthermore, in terms of portfolio diversifications, Hammoudeh et al. (2009) found that, portfolio managers should include gold and silver as assets to a portfolio that also includes oil and copper or use hedges based on those nonprecious commodities. Their results complement those of Ciner (2001) who considers gold and silver as substitutes to hedge certain types of risk. Thus, oil traders should get their signals from both fundamentals of world supply and demand but also from the actions of central banks that channel their interest rate policies through credit markets that have linkages with many sectors of the economy and translate both in real growth and inflationary expectations. Many researchers claim that the impact of crisis situation on oil price fluctuation and its volatility models. Oil is an indispensable energy resource fueling economic growth and development, and industrialized and developed economies consider it to be a key driver of their economies. Oil prices are determined by demand and supply levels, but also they are affected by sources of natural volatility including business cycles, speculative activities, and political influences (Oberndorfer, 2009; Hamilton, 2014 and Robe and Wallen, 2016). These factors have major implications for strategic decisions taken by investors, hedgers, speculators and governments, who need to be aware of phases of higher volatility, where greater levels of risk and uncertainty are exhibited in the market, thus conditioning their decision making processes (Sadorsky, 2006; Salisu and Fasanya, 2013; Zhang and Wang, 2013; Morales et al., 2018 and Evgenidis, 2018).

Crude oil prices have encountered extreme volatility over the past decades due to numerous factors, such as wars and political instability, economic and financial slowdowns, terrorist attacks, and natural disasters. This study is the first to consider the relationship between spot and future prices during four specific periods of turmoil characterized by major changes in oil prices: namely the Gulf war, the Asian Crisis, the US terrorist attack and the Global Financial Crisis. There has been a significant upsurge in research studies focused on volatility modelling, as academics and practitioners are acutely aware of the significance of understanding financial market volatility (Oberndorfer, 2009; Salisu and Fasanya, 2013; Charles and Darne, 2014; Wang et al., 2016 and Ozdemir et al., 2013).

Ozdemir et al. (2013) considered both Brent spot and futures price volatility persistence from the 1990s until 2011, finding that volatility was very persistent in both spot and futures prices. Their findings also suggest that spot and futures prices can change in an unpredictable manner in the long run, which indicates that there is little potential for arbitrage in the oil market. Similarly, Charles and Darne (2014) studied volatility persistence from 1985 until 2011. Their research suggests that structural breaks affecting the series impact the estimation of volatility persistence, which adds to our understanding of volatility in crude oil markets. Lee et al. (2013) evaluated the existence of these breaks finding them to be of great importance to individuals and firms who are concerned about how well they can manage the risks associated with frequent changes in oil prices. Krichene (2007) studied the dynamics of oil prices during January 2, 2002-July 7, 2006. Main findings were that these dynamics were dominated by frequent jumps, causing oil markets to be constantly out of- equilibrium. While oil prices attempted to retreat following major upward jumps, there was a strong positive drift which kept pushing these prices upward. Volatility was high, making oil prices very sensitive to small shocks and to news. Also Krichene (2007) extends his study of oil price dynamics by analyzing market expectations regarding future developments in these prices. Based on a sample of call and put option prices, he computes the implied risk-neutral distribution and finds it to be right-skewed, indicating that market participants maintained higher probabilities for prices to rise above the expected mean, given by the futures price. The risk-neutral distribution was also characterized by high volatility and high kurtosis, indicating that market participants were expecting prices to remain highly volatile and dominated by frequent jumps. Oil is an important and special commodity. The determinants of its price are complex. Some studies show that the rise of oil price during the two oil crises in the 1970s and 1980s was the cause of the supply factors. But the oil supply shock itself cannot fully explain the fluctuation of oil price over time (Kilian, 2008).

Narayan and Narayan (2007) were one of the first to model and forecast oil price volatility using different subsamples. The presence of structural break points confirms abnormal behavior in the series, which indicates higher uncertainty, and an elevated level of risk which should be accounted for by concerned groups of investors, speculators and policy makers. The four episodes were chosen for analysis, as they are associated with periods of significant changes in oil prices. The Gulf War showed a 100% swing in prices during the period, and the other three crises all had a minimum movement in price of over 35% during the crisis period.

During times of high uncertainty derived from terrorism, violence or radicalization activities, commodity markets, such as oil, experience a surge on prices fluctuations (Orbaneja et al., 2018), and the process of managing risks becomes of vital importance for economic agents that aim to maximize their gains while they minimize their losses (Zavadskaa et al., 2020). Gong et al. studied the link between oil prices volatility, oil shocks and financial crisis. He demonstrates the impacts of important event shocks on oil price volatility are tremendous and have a serious negative impact on the global economy. In addition to the oil specific demand shock, the dominant factor in oil price after the financial crisis is global oil inventory. By analyzing the impact of oil supply shock on the U.S. economy, Baumeister and Peersman (2013) found that oil supply shock could not explain the volatility of oil price and some of the "Great Depression" of the U.S. economy.

Diaz and de Gracia (2017) demonstrate that oil price shocks affect the returns of oil and gas companies listed on the NYSE. We use different methods to show that while volatility is affected by crisis periods, more importantly, the type of crisis influences volatility persistence. Furthermore, we test for asymmetric effects, through the T-GARCH model, and find differences between the impact of negative and positive news according to the type of crisis. The unique contribution of this paper emanates from the analysis of the four different events focusing on the behavior of the series for the whole period, and the periods before, during and after the crisis episode took place, as such a study has not been carried out in the extant literature. We have conducted a widespread review of existing research in the field and this is the first attempt to understand evidence of the behavior of oil markets in such a comprehensive manner for these types of events. Crude oil price went through intense changes in its behavior in the last five decades. This feature of the crude oil price is often ignored; such extreme shocks include the OPEC oil embargo of 1973-1974, the Iranian revolution of 1978-1979, the Iran-Iraq War of 1980-1988, the first Persian Gulf War of 1990-1991, the oil price spike of 2007-2008, and the oil price plunge of 2015. In recent years, the researchers increasingly emphasized the importance of shifts in the demand for oil and provided evidence that oil demand shocks have been important in major crude oil price shock incidences especially since the 1970 (Kilian, 2008; 2014 and 2016). More recently, the univariate or multivariate GARCH models have been used to analyze macroeconomic data, as in Chua et al. (2011) and Elder and Serletis (2010). The latter authors studied the effect of oil price shocks volatility on macroeconomic variables and vice-versa. Moreover, a number of researchers such as Reboredo (2013), Behmiri and Manera (2015), Raza et al. (2016) and Bhatia et al. (2018) investigate impacts of oil volatility shocks on commodity markets. However, all these studies are limited to models with constant coefficients. High oil price volatility creates increased uncertainty and risk in the economy. Increases in uncertainty and risk have substantial effects on the economy. The direct effects of uncertainty about oil prices on the real economy have not been studied extensively (Balcilar and Ozdemir, 2019).

Pindyck (1991) suggests that oil price uncertainty may have played a role in the recessions of 1980 and 1982. Similarly, Ferderer (1997) reports adverse effect of oil price uncertainty on output in the United States over the 1970-1990 period. Similar evidence is reported by Hooker (1996) over the 1973-1994 period. On the contrary, Edelstein and Kilian (2009) find little indication of asymmetries that would generate an uncertainty effect. They follow the approach of Elder and Serletis (Edelstein and Kilian, 2009; Elder and Serletis, 2011) and Bredin et al. (2011), and utilize a vector autoregressive (VAR) model in order to gauge the impact of oil price uncertainty. Oil price uncertainty is considered as a generalized autoregressive conditional heteroscedasticity (GARCH) process. This has been a popular approach to model macroeconomic uncertainty while investigating its effect on macroeconomic performance (Chua et al., 2011). The important role of oil price volatility forecasting in the decision making process of the aforementioned stakeholders has been highlighted in the works of Cabedo and Moya (2003), Giot and Laurent (2003), Xu and Ouenniche (2012), Silvennoinen and Thorp (2013) and Sevi (2014) as well as, Zhang and Zhang (2017), among many others. What is more, the growing interest in accurately predicting oil price volatility stems also from the intense - in crisis - financialization of the oil market. To be more explicit, the years of crisis marked the beginning of a period whereupon commodities started to behave more like financial assets as opposed to physical assets; a fact which practically implies that oil price changes have since been more closely linked to developments in financial markets (see, for example, Vivian and Wohar, 2012; Basher and Sadorsky, 2016 and Le Pen and Sevi, 2017). Thus, given the mounting importance of oil price volatility forecasting for decision making, developing appropriate forecasting practices, is in fact a challenging field of study (Chatziantonioua et al., 2019).

3. DATA AND GRAPHICAL DESCRIPTIVE

Figure 1 presents the Brent crude oil prices, in dollars, from27 November 2019 to 04 February 2020 in levels. Based on the Figure 1, pre-covis-19, oil price continues to rise. post-covid-19, the Brent price drops to the most fabulous values since 2009.

The oil prices from January 19 are a worsening of the situation on the oil market. Since this fall was preceded by a decrease which started towards the end of 2019, the date which coincides with the appearance of the first suspected cases Coronavirus crisis.

Oil price movements show some important peaks and troughs during the period of the study.

The main peaks are observed before Coronavirus Crisis. The price of a barrel has dropped by 20% since 1st January 2020. Another important peak is observed for the end of January. Date of confirmation of the transmission of the epidemic between people and similarly converge on other countries. The lowering of oil prices continues.

Faced with this drastic situation for the international economy, energy experts predict significant price implications that will drop the price of black gold around 30 dollars over several weeks or more. Just for yesterday alone, Brent oil prices fell to less than $ 34 a barrel.

Since all the price data are not stationary in the levels we transform the data into stationary series by taking first differences of the logarithmic prices and multiplying by 100. Thus, the data used in the analysis is the returns (R_t) defined as $R_t = 100 * \ln(P_t / P_{t-1})$, where P_t is the price at time t.

4. MODEL SPECIFICATION

4.1. Box-Jenkins Model Analysis: ARMA Models

In the case of a univariate time series y_t, i.e. Ψ_{t-1} the set of information fixed at time $t-1$, therefore its functional form of the conditional average of any financial time series (y_t) is defined in the equation 1 as follows:

$$y_t = E(y_t \mid \Psi_{t-1}) + \varepsilon_t \qquad (1)$$

Furthermore, $E(y_t \mid \Psi_{t-1})$ determines the conditional average of y_t given by Ψ_{t-1}.

But, in some other cases, in order to model the serial dependence and to obtain the equation that represents the function of the conditional mean, the main models of a time series, ARMA(r, s), a tool specified to properly interpret and predict the future values of the series to be studied, is used to fit the data and to eliminate this linear dependence and obtain the residual "t that is decorrelated (but not independent).

$$y_t = \mu + \sum_{i=1}^{r} \Phi_i y_{t-i} + \sum_{j=1}^{s} \varphi_j \varepsilon_{t-j} + \varepsilon_t$$

The conditional mean ARMA(r, s) is stationary when all the roots of the function $\Phi(z) = 1 - \Phi_1 z - \Phi_2 z - \ldots - \Phi_p z = 0$ are outside the unit circle.

The equation 1 determines the conditional mean ARMA(r,s) which has been analyzed and modeled in sever always. However, this mean is composed of two of the most famous specifications which are Autoregressive (AR) and Moving Average (MA) models.

In addition, to specify the (r,s) order of the ARMA process, we will use the Akaike Information Criterion (AIC), and to determine the conditional mean ARMA, we must look for the term corresponding to the minimum values of the two criteria. In our study, the choice of the order of ARMA models based on the AIC information criterion.

As we have known, dependence is very common in time series observations. So, to model this financial time series as a function of time, we start with the univariate ARMA conditional mean models. To motivate this model, basically, we can follow two lines of thought. First, for a x_t time series, we can model that the level of its current observations depends on the level of its lagged observations. In the second line, we can model that the observations of a random variable at time t are affected not only by the shock at time t, but also by past shocks that occurred before time t. For example, if we notice a negative shock to the economy, then we

expect that this negative impact will affect the economy negatively or positively either now or in the near future.

4.2. Variance Equation: Further Univariate GARCH Models

We use just five conditional variance models: GARCH, EGARCH, GJR, APARCH and IGARCH models.

4.2.1. The generalized ARCH model

The Generalized ARCH (GARCH) model of Bollerslev (1986) is based on an infinite ARCH specification and it allows to reduce the number of estimated parameters by imposing nonlinear restrictions on them. The GARCH(p,q) model can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 \qquad (2)$$

4.2.2. EGARCH model

The Exponential GARCH (EGARCH) model, originally introduced by Nelson (1991), is re-expressed in Bollerslev and Mikkelsen (1996) as follows:

$$\log \sigma_t^2 = \omega + \left[1 - \beta(L)\right]^{-1} \left[1 - \alpha(L)\right] g(z_{t-1}) \qquad (3)$$

The value of $g(z_{t-1})$ depends on several elements. Nelson (1991) notes that, to accommodate the asymmetric relation between stock returns and volatility changes (…) the value of $g(z_t)$ must be a function of both the magnitude and the sign of z_t.

4.2.3. Glosten, Jagannathan, and Runkle model (GJR)

This popular model is proposed by Glosten et al. (1993). Its generalized version is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (4)$$

where S_t^- is a dummy variable that take the value 1 when γ_i is negative and 0 when it is positive.

4.2.4. APARCH model

This model has been introduced by Ding et al. (1993). The APARCH(p,q) model can be expressed as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \left(\mid \varepsilon_{t-i} \mid -\gamma_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \qquad (5)$$

Where $\delta \succ 0$ and $-1 \prec \gamma_i \prec 1$ ($i = 1,\ldots,q$).

The parameter δ plays the role of a Box-Cox transformation of σ_t while γ_i reflects the so-called leverage effect. Properties of the APARCH model are studied in He and Terasvirta (1999a; 1999b).

4.2.5. IGARCH model

The GARCH(p,q) model can be expressed as an ARMA process. Using the lag operator L, we can rearrange Equation 2 as:

$$\left[1 - \alpha(L) - \beta(L)\right] \varepsilon_t^2 = \omega + \left[1 - \beta(L)\right] (\varepsilon_t^2 - \sigma_t^2) \qquad (6)$$

When the $[1-\alpha(L)-\beta(L)]$ polynomial contains a unit root, i.e. the sum of all the α_i and the β_j is one, we have the IGARCH(p,q) model of Engle and Bollerslev (1986).

It can then be written as:

$$\Phi(L)(1-L)\varepsilon_t^2 = \omega + [1-\beta(L)](\varepsilon_t^2 - \sigma_t^2) \qquad (7)$$

Where $[1-\alpha(L)-\beta(L)](1-L)^{-1}$ is of order $\max\{p,q\}-1$.

We can rearrange Equation 7 to express the conditional variance as a function of the squared residual.

5. EMPIRICAL FINDINGS

5.1. Identifying the Orders of AR and MA Terms in an ARMA Model

For modeling data series we used two common concepts of conditional mean: the AR process and the MA process. According to the results of the Table 1, the (r, s) order of the ARMA model is null. By setting the (0.0) pair to the moving average model and based on the Akaike Information Criterion, the appropriate choice of model for short-term conditional volatility is between the GARCH, EGARCH, GJR, APARCH and IGARCH models.

An information criterion is a measure of the quality of a statistical model. The ARMA models found are of order (0,0). We are going to eliminate the moving average model. Indeed, the volatility

models are indicated by the conditional variance in the Table 2. The data series shows strong evidence of volatility clustering, where periods of high volatility are followed by low volatility, a behavior that is consistent with common findings in the extant literature. These shocks can cause sudden shifts in the mean of oil prices. Further, they can affect the unconditional and conditional variances of oil price (Charles and Darne, 2014).

Salisu and Fasanya (2013) tested for structural breaks in the volatility of West Texas Intermediate (WTI) and Brent oil prices and found evidence in favor two structural breaks in 1990 and 2008, which correspond to invasion of Kuwait in 1990/1991 and the Global Financial Crisis in 2008. Volatility spikes are especially evident during the Gulf War and the Global Financial Crisis, as noted by Salisu and Fasanya (2013), where the returns of spot and futures oil prices show unsteady and more noticeable patterns than during the Asian Crisis and the US terrorist attack.

The parameters of appropriate volatility models results pre-coronavirus crisis and post-coronavirus crisis are resumed in Table 3.

5.2. Univariate GARCH Appropriate Models

The conditional volatility models are chosen from GARCH, EGARCH, GJR, APARCH and IGARCH.

Compare the information criterion in Table 2 within the three conditional distributions, the appropriate models of the conditional volatility of oil returns during pre and post covid-19 is EGARCH(0,2) with different parameters listed in the Table 3.

Table 1: Order selection ARMA model pre and post Covid-19 crisis

ARMA(p,q)	ARMA model pre-coronavirus		ARMA model post-coronavirus	
	AICT	AIC	AICT	AIC
ARMA(0,0)	116.655832	3.33302377	136.962888	3.91322536
ARMA(0,1)	118.522109	3.38634598	138.848038	3.96708679
ARMA(0,2)	120.511491	3.44318545	137.161422	3.91889776
ARMA(1,0)	118.502424	3.38578355	138.72098	3.96345658
ARMA(1,1)	120.48848	3.442528	140.491778	4.01405079
ARMA(1,2)	No convergence	No convergence	138.875952	3.96788435
ARMA(2,0)	120.49047	3.44258486	140.148371	4.00423916
ARMA(2,1)	No convergence	No convergence	142.096811	4.05990888
ARMA(2,2)	124.405663	3.5544475	138.039135	3.94397529

Table 2: Oil volatility returns and appropriate models

	Akaike	Shibata	Schwarz	Hannan-Quinn
Oil volatility model for the pre-coronavirus crisis				
ARMA(0,0)-GARCH(1,1)	2.868856	2.846137	3.046610	2.930217
ARMA(0,0)-EGARCH(0,2)	2.478363	2.744994	3.848322	2.570404
ARMA(0,0)-GJR(1,1)	2.779655	2.745255	3.001847	2.856356
ARMA(0,0)-APARCH(1,1)	2.707758	2.659701	2.974389	2.799799
ARMA(0,0)-IGARCH(2,1)	2.929760	2.907041	3.107514	2.991121
Oil volatility model for the post-coronavirus crisis				
ARMA(0,0)-GARCH(1,1)	3.592410	3.569691	3.770164	3.653771
ARMA(0,0)-EGARCH(0,2)	3.552355	3.504298	3.818986	3.644396
ARMA(0,0)-GJR(1,1)	3.630419	3.596019	3.852612	3.707120
ARMA(0,0)-APARCH(2,2)	3.630577	3.531235	4.030523	3.768638
ARMA(0,0)-IGARCH(2,1)	3.600357	3.577638	3.778111	3.661718

5.3. Oil Returns Volatility Pre and Post Covid-19 Crisis

5.3.1. Summary statistics

Table 4 provides the descriptive statistics including the skewness, Excess Kurtosis and Jarque-Bera (JB) statistics for oil price volatility pre-covid-19 and post-covid-19.

Kurtosis measures the pointed or flat character of the distribution of the series. The Kurtosis of the normal distribution is 3. If the Kurtosis is >3 (thick tails), the distribution is rather sharp (leptokurtic distribution); if the Kurtosis is <3, the distribution is rather flat (distribution is called platikurtic). The Kurtosis of our distribution is <3 pre-coronavirus and post-coronavirus which means that our distribution is flat.

Skewness is a measure of the asymmetry of the series distribution around its mean. The Skewness of a symmetry distribution, such as the normal distribution is zero. Positive Skewness means the distribution has an elongated tail to the right and Negative Skewness means that the distribution has an elongated tail to the left. The Skewness for the pre-covid-19 crisis oil returns volatility series is positive so the distribution is spread to the right. The trend in oil yield movements converges upwards before the crisis. The Skewness of the post-covid-19 crisis distribution is negative. This means that our distribution is biased to the left and as a result oil prices react more to a negative shock than to a positive shock against the covid-19.

The Residue normality test of oil price volatility in pre-coronavirus crisis (with JB = 0.95137) and post-coronavirus crisis situations (with JB = 0.76213) shows that the residues are normal, therefore the residues are normal (Indeed, JB <5.99). The JB test for normality shows it departs from the normal distributions.

The null hypothesis of no ARCH effects is rejected if the probability values (P-values) of these tests are greater than any of the conventional level of statistical significance (10%, 5%, and 1%). The acceptation of H_0 implies presence of ARCH effect in the series. Thus, ARCH effects are present, the estimated parameters should be significantly different from zero (the series are volatile). The presence of ARCH effects in all series oil returns suggests that the volatility associated with the returns of oil Brent market.

5.3.2. Volatility findings

Using Table 3, we found that during the pre-coronavirus crisis period, the model did report significant results. The Brent oil market is characterized by being volatile with the occurrence of large shocks, which are due to economic, political or financial causes. Our results findings therefore suggest that spot returns are more predictable based on the past volatilities, which is indicated by their higher coefficients.

This period includes pre-Coronavirus crisis of very stable oil prices, rapidly increasing prices for the Brent and then the crash that occurred during the post of the Covid-19 crisis (Table 4).

Using Table 3, we found that during the post-coronavirus crisis period, the model did report significant results. The EGARCH(0,2) model for oil returns shows higher spikes and lower persistency during direct post-Covid-19 crisis.

5.4. The Graphic Analysis: Testing the EGARCH Oil Prices Volatility during Covid-19 Crisis

The conditional mean of a series depends on the information available at time $t-1$ and is not necessarily constant. On the other hand, the conditional variance is fixed and does not depend on the information available at time $t-1$.

In fact, the hypothesis that the residues are strong white noises leads us to this result. Strong white noise implies that the residuals have a zero mean and they are uncorrelated over time. Furthermore, like the unconditional variance, the conditional variance is constant. This last condition is unrealistic because the variability over time of variances is a well-established stylized fact in finance.

Table 3: Oil price volatility models parameters: EGARCH(0,2) model pre and post crisis

Parameters	Cst (M)	Cst (V)	ARCH (α_1)	ARCH (α_2)	EGARCH (θ_1)	EGARCH (θ_2)
Pre-Covid-19	0.060208	−0.761817	1.477381	1.372341	−0.070380	−1.315734
Post-Covid-19	−0.284972	0.800655	0.660405	0.345910	0.013146	−1.777078

Table 4: Normality test oil volatility returns pre and post coronavirus

Normality test oil volatility returns pre coronavirus	Statistic	t-test	P-value
Skewness	0.070051	0.17614	0.86018
Excess Kurtosis	−0.22077	0.28384	0.77654
Jarque-Bera	0.099701	.NaN	0.95137
ARCH 1-2 test: F(2,28) = 1.5264 [0.2348]			
ARCH 1-5 test: F(5,22) = 1.7403 [0.1673]			
ARCH 1-10 test: F(10,12) = 0.99639 [0.4949]			
Normality test oil volatility returns post coronavirus	**Statistic**	**t-test**	**P-value**
Skewness	−0.036988	0.77894	0.92590
Excess Kurtosis	−0.60586	−0.60586	0.43601
Jarque-Bera	0.54328	.NaN	0.76213
ARCH 1-2 test: F(2,28) = 0.86030 [0.4339]			
ARCH 1-5 test: F(5,22) = 1.5308 [0.2211]			
ARCH 1-10 test: F(10,12) = 2.5235 [0.0658]			

The conditional mean defined in equation 1. The pre-covid-19 crisis conditional average for oil price volatility is positive (=0.6) but the post-covid-19 crisis conditional is negative (=−0.286). This shows a drop in black gold prices and also a persistence of this decline.

The conditional variance (EGARCH) defined in equation 3. The conditional variance of oil returns during the pre-coronavirus crisis is varied by 2.5 months but that of the post-coronavirus crisis varies between 2 and 4. This indicates a strong fluctuation in oil returns and also a downward trend.

Engle's idea put the conditional variance of the series of error squares as a function of delayed errors, time, parameter, and predictable variables.

The graphics of the squared residuals of the crude oil returns series shows that there is heteroscedasticity. The squared residuals <5 during pre-covid-9 crisis but >5 during post-covid-19 crisis. Indeed, post-coronavirus crisis, oil returns are very volatile.

In addition, Figures 2 and 3 plots the conditional variance ($\hat{\sigma}_t^2$) as well as the histogram of the standardized residuals ($\hat{z}_t = \dfrac{\hat{\varepsilon}_t}{\hat{\sigma}_t}$) obtained with the EGARCH(0,2) model, together with a kernel estimation of its unconditional distribution (solid line) and the N(0,1)(dotted line) in the pre post coronavirus crisis situations.

Figure 2: Conditional volatility of oil returns: Pre-coronavirus
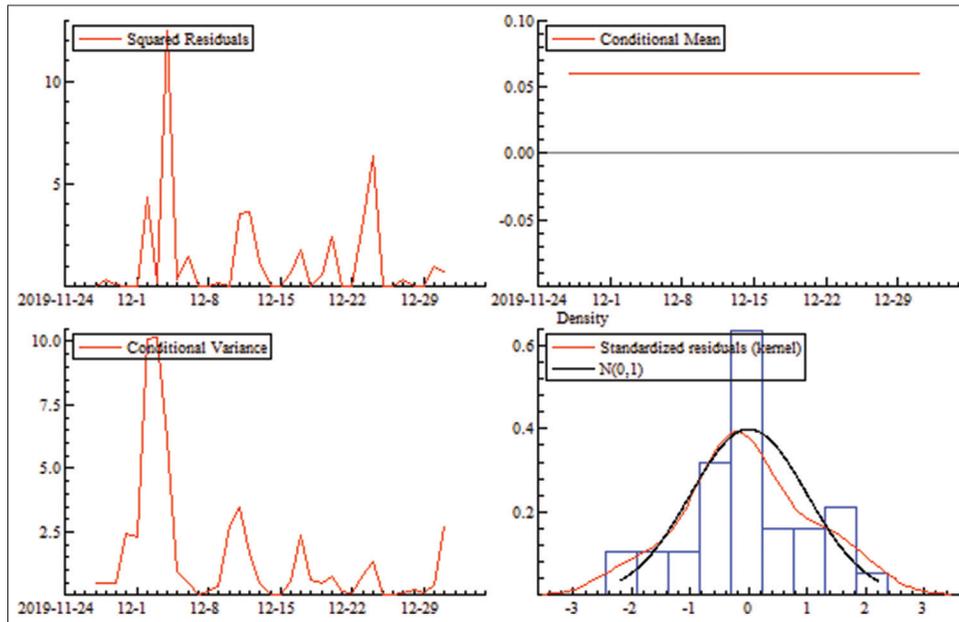
Source: Made by the author

Figure 3: Conditional volatility of oil returns: Post-coronavirus
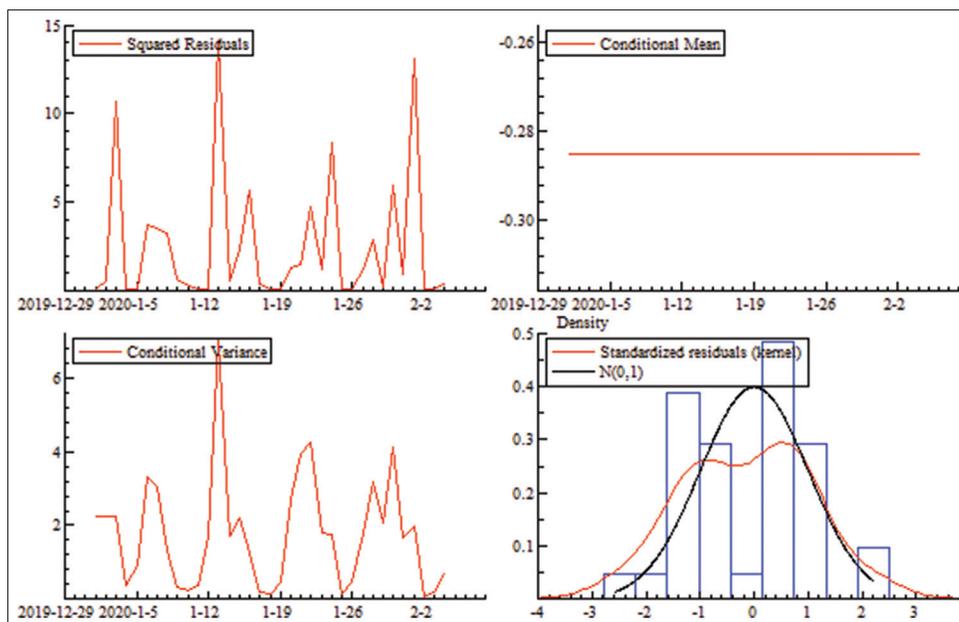
Source: Made by the author

The standardized residuals pre-convid-19 reaches 0.4, tangent to the normal on the left and close to the normal on the right (Figure 2). The standardized residuals during post-cvid-19 crisis far from normal (Figure 3).

In relation to volatility persistence, the Figures 2 and 3 are showing clear evidence of high volatility persistence between oil prices and covid-19 crisis.

5.5. Monte Carlo Simulation of Univariate EGARCH (0,2): Pre and Post Covid-19

The parameters α_1, α_2, θ_1 and θ_2 used in the simulation of the EGARCH(0,2) model are given in Table 5. The simulation number is 1 for 1000 observations.

To study the performance of this test, let us consider a first simulation study (Simulation_VR.ox). We simulate 1000 series of t = 2000 observations following N-AR(0) model with $\alpha = 0.1$, i.e. $(y_t - \mu) = \varepsilon_t$, where $\varepsilon_t \sim N(0,\sigma^2)$ and $\varepsilon_t = 0.2$. We than apply the Variance-ratio test with n = 2, 3 and 10. The 1000 realizations of the VR statistics are plotted in Figures 4 and 5 respectively of pre and post covid-19 crisis.

Table 5: Parameters of the simulated models

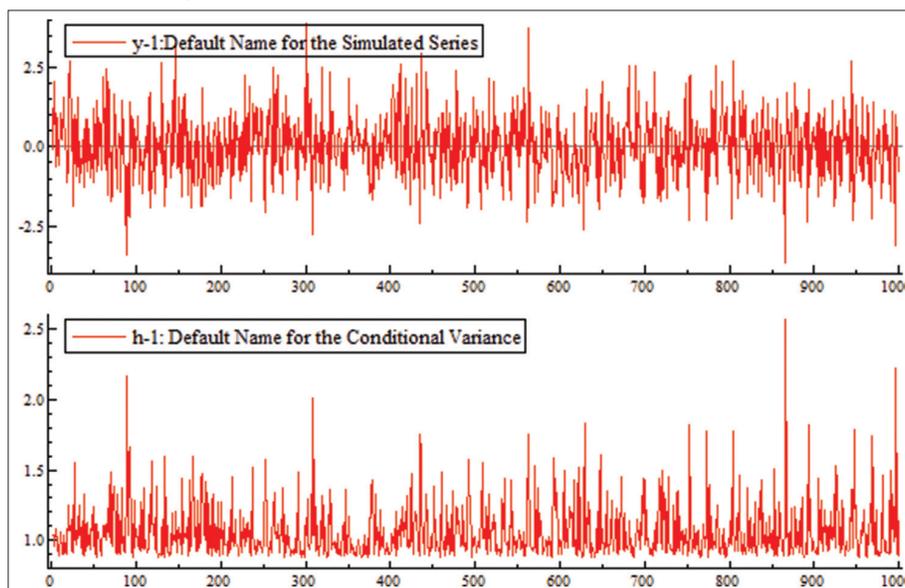| Cst (M)	Cst (V)	ARCH (α_1)	ARCH (α_2)	EGARCH (θ_1)	EGARCH (θ_2)
0.01	0.04	0.1	0.001	−0.1	0.2

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Figure 4: Conditional volatility of oil returns: Pre-coronavirus
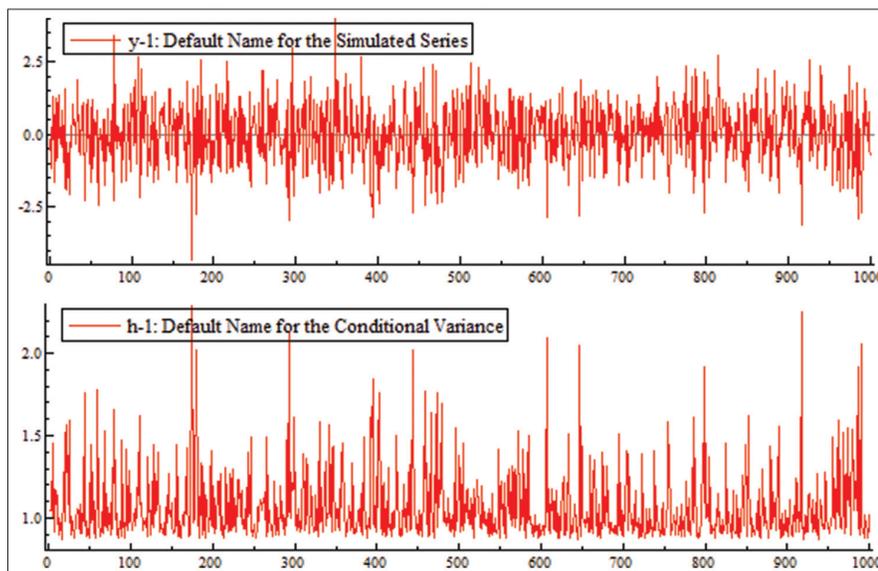
Source: Made by the author

Figure 5: Conditional volatility of oil returns: Post-coronavirus

Source: Made by the author

The asymmetry coefficient is negative which means that "the bad news" has more significant effects than "the good news." This confirms our hypothesis which states that the coronavirus crisis has a significant effect on the oil returns volatility.

The results produced by adding uncertainty due to oil returns volatility from a covid-19 crisis and using a Monte Carlo simulation (using parameters gives in Table 5) indicate that the oil field has little chance of success. According to the Figures 4 and 5 relating to the Monte Carlo simulation which seeks to test the effect of this crisis on the oil returns volatility, we can draw the following observations. We conduct a Monte Carlo simulation exercise during coronavirus crisis to investigate whether this decline is real or an artefact of the oil market. Our findings support the fact that the decline in oil prices volatility is an artefact of the covid-19 crisis.

Volatility is persistent since there are successive periods of low volatility as well as periods of high volatility. However, the periods in the post-coronavirus crisis are characterized by lower values than those recorded in the pre-coronavirus crisis.

6. CONCLUSION

Covid-19, today the risk is that of a production blockage. The coronavirus crisis poses the threat of a oil market, both for the prices and for the returns and its volatility. This paper sets out to investigate how oil price returns volatility respond in different ways to coronavirus crisis in a pre-covid-19 crisis and during post-covid-19 crisis periods. We use a long time series of daily oil Brent price data and its returns covering the period from 27 November 2019 to 04 February 2020, with each firm having 70 days. Oil prices plunge in the face of the coronavirus.

The risks involved with high levels of volatility in oil prices influence the decision-making process of investors, speculators and policy makers. The findings from this study show that during times of Coronavirus crisis and direct oil price volatility disruptions (such the ones that took place during the pre-coronavirus and the post-coronavirus attack period), the series exhibited higher volatility spikes. Based on the information criteria, the appropriate model for oil returns volatility is EGARCH(0,2) model.

This approach indicates low future volatility prices, strongly suggesting the unviability of the oil market when Monte Carlo Simulation were applied. Our empirical analysis was based on the Brent oil prices and its returns volatility. We conduct a Monte Carlo simulation exercise during coronavirus crisis to investigate whether this decline is real or an artefact of the oil market. Our findings support the fact that the decline in oil prices volatility is an artefact of the covid-19 crisis.

Our initial results bring some useful evidence on the important implications derived from the new role that coronavirus crisis decreases could exercise oil market. This is consequently a topic worthy of future research. Subsequent studies could use Multivariate GARCH Models (namely the scalar BEKK, diagonal BEKK, Risk Metrics, CCC, DCC, OGARCH and GOGARCH

models) modeling and also data with different frequencies (weekly and monthly); this would provide more evidence on the real importance of oil returns volatility during, pre and post covid-19 crisis.

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