ANALYSIS AND MODELING OF NYSE ARCA OIL & GAS STOCK INDEX RETURNS

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Abstract: *Through this study we have analyzed and modeled the returns of the NYSE ARCA OIL & GAS stock exchange index (symbol XOI). This index, previously called the AMEX Oil Index, comprises 20 of the most important oil companies operating in the oil industry. For a better overview, we have presented the factors that influence the price of oil and the effects of lowering its price on oil companies and on the economy of oil exporting states. The study was conducted between August 1983 and April 2017 on a daily frequency of data. In trying to identify the most appropriate predictive model for 10 periods, we tested several ARIMA, ARCH and GARCH models. Based on the AIC criterion, we selected the ARMA (2,1) - GARCH (1,1) model, which we predicted for the next 10 periods, the series of returns and the conditional volatility of the studied index. Predicted conditional volatility indicates a slight increase for the 10 periods of time, while the predicted series of returns evolve downward. The study thus confirmed the theoretical hypothesis that increased volatility in stock markets occurs when price declines are recorded, the impact of negative news on stock markets being stronger than positive news.*

Keywords: *returns, volatility, Garch model, stock index, prediction*

JEL classification: C32, C53, Q43

1. Introduction

Volatility of the capital market is a permanent source of stress for participants in the capital markets. Holders of financial assets seek to protect themselves against risks by diversifying their portfolio (national and / or international) or through hedging operations (using equity-specific instruments such as futures, forward, options, etc.).

The diversity and complexity of traded financial instruments has led to a sharp rise in capital market volatility over the past 20 years (as evidenced by the evolution of S&P 500) as compared to macroeconomic volatility at least in the US and Europe declining, reduced than the one 50 years ago (Bookstaber, 2007).

Financial asset prices are constantly in the public attention, regardless of whether or not our daily activity is directly related to stock markets. Evolution of stock indices, foreign exchange rates, oil and gold prices, interest rates are reported daily in the press and television.

Price variations of these assets may have a special amplitude, both positive and negative. For example, the price of oil climbed to 147 USD / barrel in July 2008, reaching $ 32 / barrel in December of that year and then rising to $ 60 in October 2009.

Detailed knowledge of the peculiarities and correlations between the evolution and volatility of oil prices (and other raw materials), foreign exchange rates has an obvious practical utility for economic operators in various sectors, for investors in the financial markets (natural and legal persons), for fund managers (mutual, pension), insurance companies, etc.

Aizenman J. and B. Pinto (2005) published a Volatility and Crisis Management Guide, which includes studies on the macroeconomic volatility-economic growth relationship, exchange rate volatility, interest rate, etc.

Volatility of oil prices has become a permanent source of uncertainty in the capital markets and beyond. The attempt to predict the evolution of the oil price is difficult, because are many factors that influence it: the demand-supply ratio (which has seen major changes in recent years), oil stocks, refining capacity utilization rates, quotations on futures markets, monetary factors such as the interest rate and the exchange rate of the dollar, along with geopolitical factors and psychological factors.

In January 2015, oil price volatility peaked in the last five years. Increased oil production in the US (as a result of the use of hydraulic fracturing and horizontal drilling technology), OPEC Gambit in November 2014, additional production resulting from oil shale exploits in Canada, continued production in Iraq (in spite of political tensions) the recovery of production in Libya, coupled with the decline in world oil demand (China becoming the main importer of black gold) has led to a sharp depreciation of oil prices in 2015.

The price of oil is not only influenced by oil transactions but also by derivative transactions with underlying asset the price of oil (derived products introduced on the American market since 1983).

The speculators' orientation towards the commodity market has made it more volatile than the currency and capital markets, which is not normal

Decreasing oil prices has a positive impact on the economies of oil importing countries: China, Japan, India, Indonesia, Turkey, Ukraine etc.

The impact on Romania (according to the NBR estimates) is insignificant, of only 2.3% of GDP, thanks to the domestic production. But the reduction in oil prices has an influence on inflation in our country. The NBR estimated that a 10 percent drop in the Brent crude price would result in a fall in gasoline and diesel prices by 3.3 percent for a quarter from the fall.

The transmission is marginally asymmetric, meaning that an increase in the price of oil is transmitted more quickly and with an higher amplitude in the price of the pump than in the case of a decrease in the price. The indirect effect of this decline is that about 17% of the price change of fuels is transferred to the consumer goods production prices over a one-year horizon. The change in the production prices of consumer goods is transferred in the proportion of about 70% to the basic inflation over the same one-year horizon. Basically, the 10% crude price depreciation dropped 0.2 percentage points to the CPI inflation rate over a one-year horizon.

The impact has been negative on oil-exporting countries such as Venezuela, Nigeria, Angola, Iran, which have experienced serious problems as a result of lower oil prices.

These countries do not have large foreign exchange reserves (such as Norway, Canada, Persian Gulf countries, except Iraq and Iran) and are at risk of high inflation, depreciation of the national currency, increasing deficits and, in some cases, becoming insolvent.

We have witnessed bankruptcies among small oil companies, but also a widespread trend of mergers and acquisitions between different companies in an attempt to consolidate prosperity in the market. Thus, Halliburton acquired Baker Hughes (a smaller rival) for $ 34.6 billion. Shell bought British Gas (BG) for $ 70 billion. It was the largest transaction in the oil industry over the past ten years, with the new company surpassing Chevron as market value. MOL Group also bought ENI Romania, including a number of 42 gas stations that are now operating under the MOL name.

The visible effects of lower oil prices are:

- rapid appreciation of USD and depreciation of currency from emerging economies (those dependent on raw material exports);
- the decline in oil-related financial assets (the possibility that some industrial operators will fail, with negative influences on the stability of credit banks and the spread of a chain reaction on the credit market and possible expansion in other sectors).
- growing the preoccupations of exporting countries to get rid of oil dependence. An example is Saudi Arabia, the world's largest oil producer, which in 2015 recorded a record budget deficit of 98 billion dollars, about 20 percent of GDP, the effect of oil price declines in recent years. As a result, Saudi Arabia has decided to list, in 2018, an 5% of Aramco Saudi, the largest oil company in the world, with reserves of about 265 billion barrels, accounting for 15% of world oil deposits. At a $1,000 billion Aramco rating, the 5% of the company would bring Saudi Arabia $ 50 billion.

Starting in 2016, we witnessed oil price rises, with the upward trend continuing until now. This is reflected in the agreement between OPEC member states to reduce oil supplies (which other countries like Russia have joined), the Iranian population protests (the world's third world oil producer in OPEC), the stagnation of operating activity in USA, etc

Volatility of financial assets is a variable that is constantly pursued by stock market participants. For example, in US markets we have volatility indices for commodities such as: NYMEX Crude Oil (WTI) Futures Index (CVF) for oil, COMEX Gold Volatility Index Futures (GVF) for gold, etc.

The paper is organized in four main areas: review of scientific literature, research data and methodology, results and conclusions of the study.

2. Literature review

Analyzing and forecasting the evolution of stock indices has been the subject of numerous previous analyzes, testing emerging and developed stock indices over different periods of time for different data frequencies and using various study models.

The ARMA model was proposed by Box and Jenkins (1976) and was used to study the volatility of financial assets. It was based on the hypothesis (proven later to be erroneous) that the price series of financial assets have a constant variance.

Bollerslev (1986) using ARMA and EGARCH models to study the American stock market.

Agray (1989) tested ARCH, EMWA and GARCH (1,1) to identify what are the time series properties for the expected earnings rate of US assets. The study revealed that GARCH (1.1) is the winning model.

The conclusion that the volatility of the S & P 500 index is more pronounced in times of recession as compared to expansion is the result of the study by Sill (1993).

Hansen and Lunde (2004) showed that a model Garch (1.1), which uses three parameters in the conditional variance equation, is sufficient for modeling the financial time series.

Franses and Djik (1998) made volatility predictions by applying different models such as Random Walk, GARCH (1.1), QGARCH (1.1) and GJR-GARCH (1.1) for stock indices in different countries : Germany, Italy, the Netherlands, Spain and Sweden.

Count (2001) surprised the "stylized properties" of the financial time series, such as the leptocurtotic character, the volatility clustering effect, the leverage effect, the fat tails, etc.

The GARCH-M model was tested by Pyun and Aruza (2002) for US stock indices (1926-1997).

The series of studies was continued by Harq et al. (2004). For 10 markets in Africa and the Middle East, they tested the Random Walk, ARMA and GARCh-M

The persistence of volatility on the Portuguese capital market (using the PSI20 index) was conducted by Caido (2004). The analysis revealed that the mean reverting is recorded for low frequencies (daily), but not for high frequencies.

Chang's analysis (2006) also came up with the same result. The leverage effect (the effect that news has on volatility) was first observed by Black (1976). He found that the impact of negative news on volatility is much higher than the positive ones.

Zhou (2009) concluded that the ARMA (0.2) -APARCH (1.1) model used to predict the evolution for the next 10 periods of conditional volatility of the US index S & P500 was better than ARMA (0.2) - GARCH (1.1).

Beckers and Strom (2014) made predictions over time for the Brent oil price using the Random Walk and VAR models. For short periods of time (12-24 months) and for increased volatility periods (starting in 2008), the most successful model proved to be the VAR model.

Effendi (2015) conducted an analysis of the most performing ARCH / GARCH models for the JKSE (Jakarta Composite Index) and stock indices from developed countries such as Nasdaq, FTSE and STI. The conclusion of the study was that the GARCH model (1.1) was most appropriate for the NASDAQ index.

We will continue the series of these studies, with that of the NYSE Arca Oil & Gas oil index over an extended period of time (August 1983 - April 2017). We will compare its evolution with the price of WTI oil and we will seek to highlight the causal relationship between these two variables.

3 Data and methodology of research

Formerly called the AMEX Oil Index, this index traded at NYSE, has 20 major oil companies.

The index, which measures the performance of the oil industry, was launched on August 27, 1984, with a benchmark of 125 points.

The index is calculated and maintained by NYSE Arca, which can change its component so that it reflects as accurately as possible the real situation of the oil industry and its component to find representative companies in this industry.

Table 1 - Oil companies included in the Arca Oil & Gas index

	Symbol	Company Name
1	CVX	Chevron Corporation

2	PBR	Petróleo Brasileiro S.A. – Petrobras
3	PTR	PetroChina Company Limited
4	OXY	Occidental Petroleum Corporation
5	STO	Statoil ASA
6	BP	BP p.l.c.
7	SU	Suncor Energy Inc.
8	MRO	Marathon Oil Corporation
9	MPC	Marathon Petroleum Corporation
10	COP	ConocoPhillips
11	RDS/A	RDS/A
12	NBL	Noble Energy, Inc.
13	HES	Hess Corporation
14	XOM	Exxon Mobil Corporation
15	TOT	TOTAL S.A.
16	APC	Anadarko Petroleum Corporation
17	EC	Ecopetrol S.A.
18	PSX	Phillips 66
19	VLO	Valero Energy Corporation
20	EOG	EOG Resources, Inc.

Source: Yahoo Finance

For the purpose of this study, we used daily data for the period August 26, 1986 to April 19, 2017. The daily data series was collected from www.yahoofinance.com. In order to get a first picture of NYSE Arca Oil & Gas (symbol XOI) stock index, we switched to the graphical representation of its daily data series parallel to West Texas Intermediate (symbol WTI).

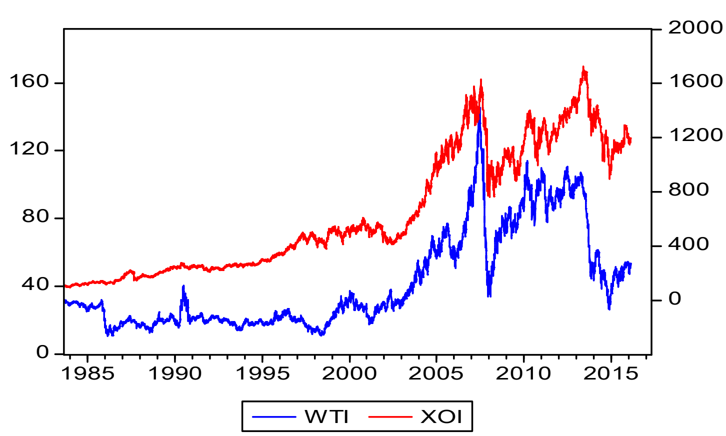

Figure 1 - Graphs of NYSE Arca Oil & Gas Index and West Texas Intermediate

Analyzing the XOI time series, it can be seen that it deviates significantly from the stationary property. The trend was upward until 2008 when obvious turmoil due to the financial crisis. After the extremely steep decline registered in 2008, the ^ XOI series returned to growth (2009-2013). In 2014, we witnessed sharp declines in the quote, but the situation recovered in 2016, and growth continuing until today.

After the graphical analysis, we also carried out a simple, descriptive statistical analysis of the initial data sample (Table 2). The statistical and econometric analysis program R allows such an analysis through the command "basicStats (XOI [, 5])".

Table no. 2 - Descriptive statistics for the initial data series

	^XOI
Nr obs.	8483
Mean	642.6897
Median	484.5800
Maximum	1726.2200
Minimum	94.92000
Std. Dev.	457.3986
Skewness	0.565685
Kurtosis	-1.147608
Jarque-Bera	918.0070
Probability	0.000000

Author's calculations

It can be seen that the NYSE Arca Oil & Gas data series is not normally distributed (Table 2). Normal distribution is characterized by Skewness = 0 and Kurtosis = 3. In our case, the average ($ 642.6897) does not coincide with the median ($ 484.58), the series being asymmetric to the left and having a negative kurtosis (k=-1.147608), indicating a more flattened distribution (platikurtotica) than a normal distribution.

Generally, in the case of real financial asset prices, kurtosis usually has values> 3, that is, a leptocurtotic distribution. Because we noticed that the price series is non-standard, it was necessary to stationarized the data before continuing the study.

The most efficient and simple way to stationarized time series of stock data is to apply the first order difference, in our case passed from price analysis to return analysis.

When we talk about returns, we can consider the calculated returns as the percentage difference between the current price and the previous price, but we can also discuss the compound compound returns, in which case we use the natural logarithm.

$$r_t = \ln(1+R_t) = \ln\frac{P_t}{P_{t-1}} = \ln(P_t) - \ln(P_{t-1})$$

We continued to work with returns and that is why we switched to differentiating the XOI data series, obtaining the DXOI series of returns.

For a better image, we did the same thing with the WTI series (DXOI). The return series for the two financial assets are presented in the following picture (Figure 2).

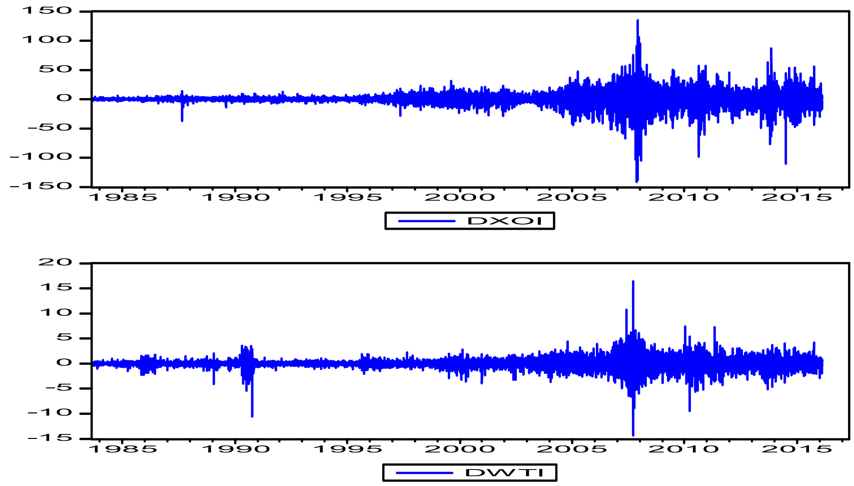

Figure 2 - Graphic representation of the Nyse Arca Oil & Gaz index and West Texas Intermediate

In order to better know the series of data obtained by logarithm and differentiation we again called the descriptive statistics of the series, applying the following code in the program R: basicStats(lXOI).

The result is presented below and indicates the main statistical properties of the new time series obtained by differentiation and logarithm.

Table no. 3 - Descriptive statistics for the return series

	^XOI
Nr obs.	8482
Mean	0.000279
Median	0.000444
Maximum	0.154457
Minimum	-0.225771
Std. Dev.	0.014258
Skewness	-0.742205
Kurtosis	17.696261
Jarque-Bera	119128.6
Probability	0.000000

Author's calculations

It can be noticed that this time the data series is not normally distributed. The kurtosis value is positive and is greater than 3, indicating a leptokurtotic distribution, specific to the real data series of financial assets (Table 3).

On the series of returns we apply the statistical test t to test whether the average of the sample is statistically significantly different from zero. The results of the t test (p-value 0.07121) cause us to accept the null hypothesis that the mean is zero.

This finding confirms the results of previous studies conducted by different authors on different types of stock markets, according to which, for high frequencies (intraday or daily data), the series of returns are very close to zero.

3.1 Testing for ARCH effects

Studying and forecasting volatility (volatility perceived as a source of risk by investors) has always been a research topic for researchers. The first model to estimate the volatility of financial assets was the ARMA model proposed by Box and Jenkins (1976).

The model was based on the hypothesis (proven later to be erroneous) that the price series of financial assets have a constant variance. The model was not able to capture certain peculiarities of the financial time series such as leptocurtotic character, volatility clustering, fat tails, leverage, etc.

In order to solve this limitation, Engle (1982, pp. 987-1008) proposed the Autoregressive Conditional Heteroscedasticity Model (ARCH), the model in which the variance depends on the previous squared error series, at its base being the empirical observations of the change in time of the volatility and its dependence on the previous values. In building an ARCH model are used two equations:

- first for conditioned media, the equation of evolution of the return of the financial asset
- the second for the conditioned variance, the volatility equation.

The limitation of this model was given by the weight of the estimation of its coefficients. Bollerslev (1986, pp. 307-327) improved the previous model, proposing the GARCH (p, q) model (Generalized Autoregressive Conditional Heteroscedasticity):

$$r_t = \beta_0 + \sum_{i=1}^{m} \beta_{1,i} L^i r_t + \sum_{j=1}^{n} \beta_{2,j} L^j \varepsilon_t + \varepsilon_t$$
$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1,i} L^i h_t + \sum_{j=1}^{q} \alpha_{2,j} L^j \varepsilon_t^2$$

In previous equations, rt (the individual asset yield) describes an ARMA process (m, n) while ht (volatility) is a process of ARCH (q) and GARCH (p). The condition to be met by the parameters of the ht equation, for the process to be covariant stationary is:

$$\sum_{i=1}^{p} \alpha_{1,i} + \sum_{j=1}^{q} \alpha_{2,i} < 1$$

Based on this model, it is attempted to predict the volatility of the next period, based on the long-term average of the variance, based on the previous variance (represented by the term GARCH) and the volatility observed in the previous period (expressed by the term ARCH).

The sum of the ARCH and GARCH coefficients (α1 + α2) represents the persistence of conditioned volatility. The terms ARCH and GARCH must be subunitary and positive.

When the sum of these coefficients is greater than 1, we are dealing with an explosive process that can be modeled using the IGARCH model. Next, I will test the existence of heteroskedasticity (ARCH terms). For this we will test the autocorrelation of the square errors of the regression equation.

The existence of this autocorrelation of square errors will indicate the presence of ARCH terms. The results of the test (p-value = 6.786e-08) lead us to reject the zero hypothesis, that of the inexistence of the data correlation. In conclusion, we have autocorrelation of the square errors until lag 20.

The existence of ARCH terms has been tested with the help of autocorrelation and partial autocorrelation functions, their grouped graphic representation being presented below

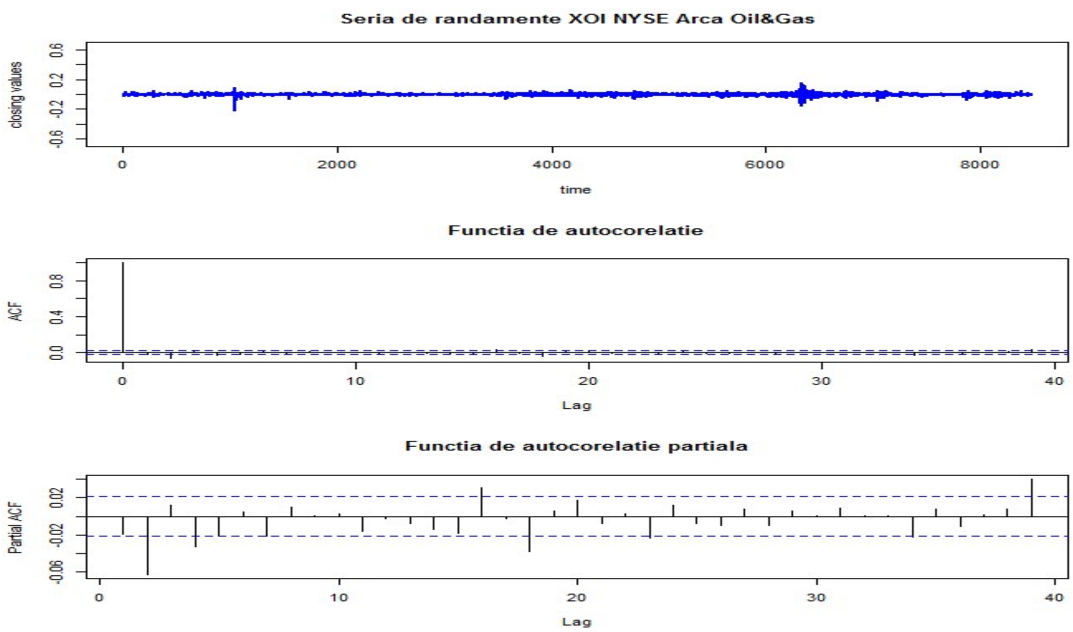

Figure 3 - Graphic representation of return series, autocorrelation function (AC) and partial autocorrelation (PAC) for the XOI index

From the graphical representation of the autocorrelation function, we can observe the presence of ARCH terms. From the same representation we can see that the data series values are autocorrelated to lag 20 and as such we will introduce an ARMA term to explain the autocorrelation on the linear side of the model.

We will still use a model that will contain an ARMA term. The code used in the R program for this operation is the following: m1=arima(lXOI,seasonal=list(order=c(0,0,1), period=5), include.mean=F). I extracted the residues from the above equation, m1, using the Box.test () test for square errors. "at =m1$residuals, Box.test(at^2,lag=12,type='Ljung')". The test results (p-value = 0.004385) presented above lead us to reject the zero hypothesis (H0: there is no autocorrelation up to lag 20). In conclusion, the square errors are autocorrelated to lag 20.

4. Results and interpretations

4.1. Determining the size order for the ARCH process

We then tested several ARCH, GARCH (with different lags) to be able to select the most appropriate.

The selection was made according to several criteria:

• the lowest information criterion (AIC)

• error values,

• the significance of the coefficients from a statistical point of view,

• fulfilling the condition that the process is stationary in the covariance.

It is necessary that the sum of the coefficients be subunit so that the process returns to the average, to be mean reverting. Otherwise, the data series is explosive and could not be modeled by GARCH models, but by IGARCH models. If the sum of the two coefficients is very close to 1, it means that the processes that generate these series return very slowly to the long-term mean.

To estimate the AR and MA process, we ran several autoregressive moving average (ARIMA) models, univariate models by which the dependent variable is modeled according to its own observations. For each model I used the stationary initial series. ARMA models were compared using the AIC information criterion. The results of model testing are synthesized below (Table 4).

Table 4 - Models tested and value of the AIC informational criterion

model 1	ARMA (0,5)	GARCH(1,1)	Distrib “std”	AIC - 6.065236
model 2	ARMA(1,1)	GARCH(1,1)	Distrib “std”	AIC - 6.065150
model 3	ARMA(1,1)	GARCH(1,1)	Distrib “sstd”	AIC - 6.065383
model 4	ARMA(1,2)	GARCH(1,1)	Distrib “std”	AIC - 6.065878
model 5	ARMA(1,2)	GARCH(1,1)	Distrib “sstd”	AIC - 6.066004
model 6	ARMA(2,1)	GARCH(1,1)	Distrib “std”	AIC - 6.065869
model 7	ARMA(2,1)	GARCH(1,1)	Distrib “sstd”	AIC – 6.066087
model 8	ARMA(0,2)	GARCH(1,1)	Distrib “std”	AIC – 6.064819
model 9	ARMA(0,2)	GARCH(1,1)	Distrib “sstd”	AIC – 6.064901
model 10	ARMA(0,2)	GARCH(2,1)	Distrib “std”	AIC - 6.064545
model 11	ARMA(0,2)	GARCH(2,1)	Distrib “sstd”	AIC - 6.064627
model 12	ARMA(0,1)	GARCH(1,1)	Distrib “std”	AIC - 6.064712

Author's calculations

4.2. Selection of the best model

Based on the above-mentioned selection criteria and the Akaike Informational Criteria with the lowest value (-6.066087), the ARMA (2.1) was the most advanced model.

This model combines both autoregressive lags of the dependent variable and the average mobile process error.

The ARMA model (2, 1) indicates that the present price of the XOI is due to the evolution of the previous days (day 1 and 2), but also to the shocks of the day 1.

Thus, the current price of XOI according to the ARMA process is influenced positively by the price of one day ago and in the negative sense of the price of 2 days ago, while the shocks of the previous day (day 1) have a negative impact on it (Table 5).

Table 5 Estimation of the ARMA Model (2,1) - GARCH (1,1)

Coefficients	*Value (p-value)*
mu	*5.607e-05 (0.07712)*
ar1	*9.024e-01 (< 2e-16)*
ar2	*-3.790e-02 (0.00124)*
ma1	*-8.837e-01 (< 2e-16)*
omega	*1.226e-06 (7.5e-06)*
alpha1	*6.115e-02 (< 2e-16)*
beta1	*9.331e-01 (< 2e-16)*
skew	*9.701e-01 (< 2e-16)*
shape	*7.279e+00 (< 2e-16)*

Author's calculations

From the previous table we can see that the two coefficients of the equation for the variant are positive and subunitary.

The sum of the coefficients is subunit (0.994247) but very close to 1, which means that the process returns very slowly to the long-term mean.

Statistical analysis of coefficients largely validates this model, most of which are statistically significant (at a 1% specification level), with the exception of the MU which is statistically significant at a specification level of 10%.

In order to see if the selected model is correctly specified, we will pass the standardized residue analysis**.**

4.3. Analysis of the ARMA (2.1) -GARCH (1.1) selected model errors.

If the model is correctly specified, standardized residues should no longer have serial correlation, conditional heteroskedasticity or any other non-linear dependence.

From testing the selected model, the information summarized in the following table was obtained (Table 6).

Table 6 Standardized residue analysis of ARMA (2,1) -GARCH (1,1)

Log Likelihood	25735.28
Jarque-Bera Test	*10814.49 (0)*
Ljung-Box Test R Q(10)	*12.01626 (0.2839698)*
Ljung-Box Test R Q(15)	*16.78606 0.331814*
Ljung-Box Test R Q(20)	*23.46582 (0.2665046)*
Ljung-Box Test R^2 Q(10)	*9.052129 (0.5271636)*
Ljung-Box Test R^2 Q(15)	*11.01068 (0.7518366)*
Ljung-Box Test R^2 Q(20)	*16.82529 (0.6642872)*
LM Arch Test	*10.31135 (0.5886661)*

Author's calculations

For a better image, we estimated the ACF and PACF functions of standardized residuals of the model and applied the Q test (Ljung-Box test) to investigate the existence of the serial correlation in residues. It can be noticed that they are no longer correlated starting with the second lag (Figure 4).

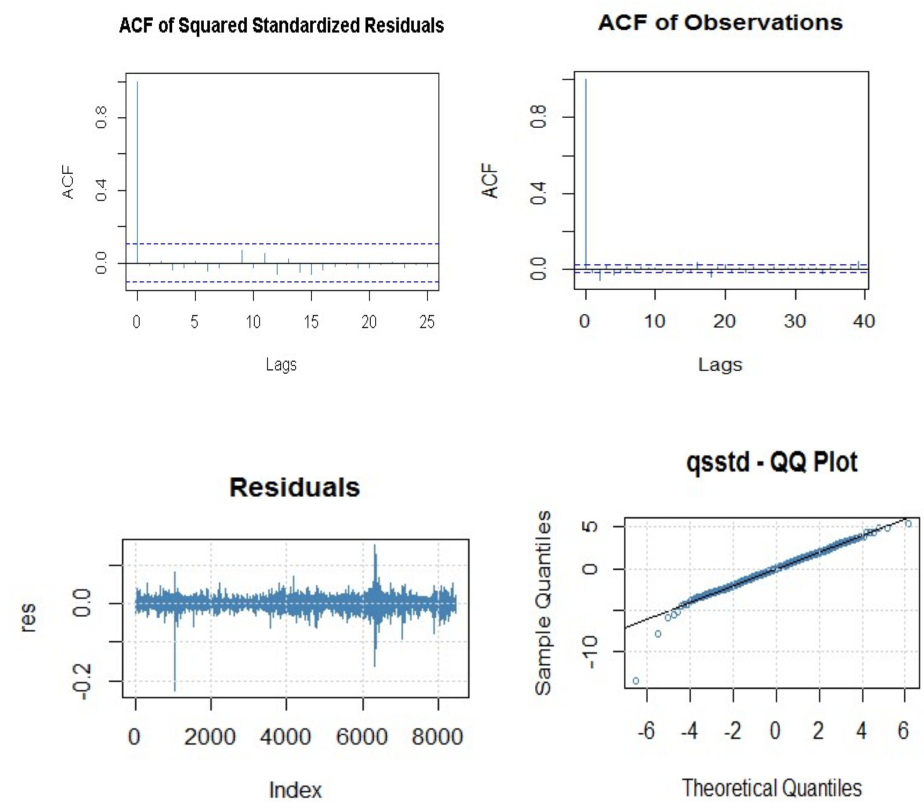

Figure 4. The graphical representation of the residue series, of the autocorrelation function for the standard yield and standardized quaternary residue and the quantitative

With LM Arch Test, we tested the existence of other ARCH effects that were likely to remain in the residuals.

A correctly specified pattern should remove these effects from the residuals series. The LM Arch Test result (Table 5) indicates a p-value of 0.5886661, which determines us to accept the zero hypothesis, that of the absence of ARCH effects in standardized residuals.

The graph with the ACF representation for standardized residuals comes to confirm the same thing we do not have ARCH effects in residuals.

The Jarque-Bera test presented in the model (table 6) has a p-value 0 indicating that model residuals are not yet distributed normally.

Applying the Q test (Ljung Box test) we tested the presence of the linear correlation in the square residuals of the model. The test results indicate a p-value = 0.5887, which shows that there is no autocorrelation in the squared residuals up to lag 20. Also, it can be noticed that the residuals do not show partial autocorrelation (Figure 5).

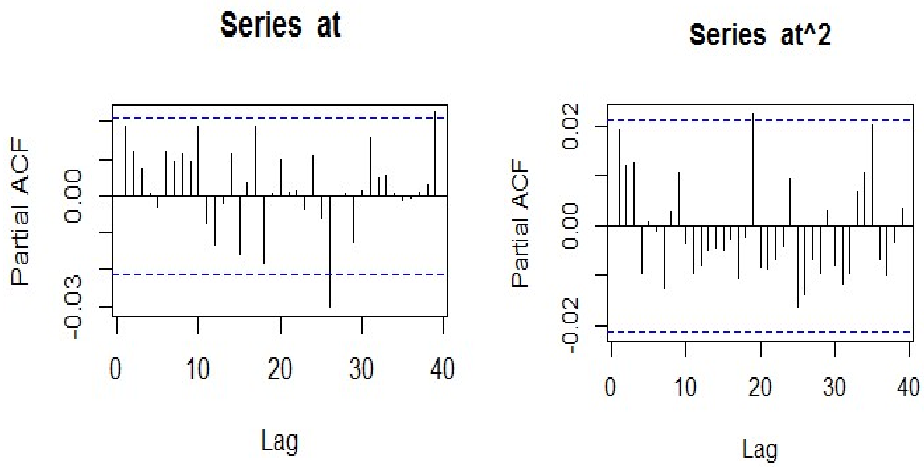

Figure 5. Graphic representation of the partial autocorrelation function for standardized residuals and standardized squared residuals of the model

Finding that all conditions are met, we can conclude that the ARMA (2.1) -GARCH (1.1) model is the correct one (the only reserve being the statistical significance of the mu coefficient). We will continue with predicting mean and conditional volatility over the next period using this model.

4.4. Perform the prediction using the selected model

Based on the daily stationary data and the most appropriate model, in our case m8, ARMA (2.1) -GARCH (1.1) we will make the prediction for the next 10 days.

Table 7 - Forecast for the next 10 periods of yields and volatility adjusted using the ARMA (2.1) -GARCH (1.1)

	MeanForecast	MeanError	Standard Deviation
1	0.000565921	0.01014788	0.010148
2	0.001167423	0.01018081	0.010179
3	0.001088069	0.01021394	0.01021
4	0.000993664	0.01024639	0.010241
5	0.000911484	0.01027824	0.010271
6	0.000840905	0.01030955	0.010301
7	0.000780331	0.01034038	0.010331
8	0.000728345	0.01037077	0.01036
9	0.00068373	0.01040076	0.01039
10	0.000645442	0.01043039	0.010419

Author's calculations

Media prediction is represented by the first column, while the volatility of this series is represented by the third column (standard deviation of the XOI data series). From the previous table, it can be seen that the predicted volatility for the next 10 periods is growing slightly.

The conclusion of the empirical observations was that financial market actors perceive volatility differently, depending on the daily fluctuation of stock prices (decline or growth). It has been noticed that volatility increases when stock prices decrease and remain low when trading prices increase.

5. Conclusions

We can conclude that the NYSE Arca Oil & Gas returns series follows an ARMA process (2.1) and that GARCH (1.1) is the most appropriate model for volatility modeling. So we used ARMA (2.1) -GARCH (1.1) model to estimate returns and volatility for the next 10 periods. The study found that future conditional volatility increased slightly amid a downward trend in the NYSE Arca Oil & Gas index. The time series included in the study was fairly long, from August 1983 to April 2017, the stock index being analyzed through periods of stability or slight growth (1983-2004), periods when the trend was much more pronounced (starting with the year 2004) and culminated in 2008 when the highest volatility was recorded for both the studied index and the WTI oil price. The WTI oil price influences the profitability of the component companies of this index (Figure 1). For both financial assets, volatility was maintained in the post-crisis period. The situation has improved since 2016, with the upward trend still being maintained. It would be recommended that the study be resumed over more recent periods using other models and frequencies of the time series to reflect as accurately as possible current market trends, all of which are to be a useful tool for investors in the process of substantiating the investment strategy.

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