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Value at risk in the oil sector: an analysis of the efficiency in the measurement of the risk of the α-stable distribution versus the generalized asymmetric Student-t and normal distributions

Valor en riesgo en el sector petrolero: un análisis de la eficiencia en la medición del riesgo de la distribución α-estable versus las distribuciones t-Student generalizada asimétrica y normal

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Abstract
In the oil sector, value at risk (VaR) can be used to quantify as best as possible the maximum oil price changes, because these have an impact on economic activity and finds evidence of its importance in explaining movements in the stock returns (Sadorsky, 1999). With this purpose, in this paper we quantify the VaR of three types of oil (Brent, WTI and MME) and analyze the performance of the one-day VaR estimation by Kupiec test considering GARCH models with three alternative distributions in the innovation process: stable, Student-t generalized and normal in a period of high volatility. The results of the performance evaluation of the model based on the Kupiec statistic indicate that the VaR-stable model is a more robust and accurate model for both confidence levels than those based on the generalized asymmetric and normalized Student t-distributions. This result is crucial in the financial sector, because it directly impacts the provision of reserves necessary to face potential losses.

JEL code: G17, C22, C13
Keywords: Stable distributions; Generalized skew t distribution; Value at risk (VaR); GARCH

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Resumen

En el sector petrolero, el VaR se ha implementado con el objetivo de cuantificar lo mejor posible los movimientos extremos de los precios del petróleo, debido a que estos repercuten la actividad económica y afectan significativamente los movimientos en el mercado accionario (Sadorsky, 1999). Con este propósito, en esta investigación cuantificamos el VaR considerando tres tipos de petróleo (Brent, WTI y MME) y analizamos el desempeño de la estimación del VaR a un día mediante el estadístico de Kupiec considerando modelos GARCH con tres distribuciones alternativas en el proceso de innovación: estable, t-Student generalizada asimétrica y normal en un período de alta volatilidad. Los resultados de la evaluación de desempeño del modelo basado en el estadístico de Kupiec señalan que el modelo VaR-estable es un modelo más robusto y preciso para ambos niveles de confianza que los basados en las distribuciónes t-Student generalizada asimétrica y normal. Este resultado es crucial en el sector financiero, debido a que impacta directamente en la previsión de reservas necesarias para afrontar potenciales pérdidas.

Código JEL: G17, C22, C13
Palabras clave: Distribución estable; Distribución t-Student generalizada asimétrica; Valor en riesgo (VaR); GARCH

Introduction

Since the liberation of the energy sector in 1970, oil prices and their high volatility have generated significant concern for consumers, producers, and governments, as well as a growing academic interest in studying this important economic variable in risk management. Several factors affect the oil price, the main ones being the policies of the Organization of the Petroleum Exporting Countries (OPEC)[1], military conflicts, geopolitical tensions, natural disasters, imbalances between supply and demand in international markets, among others.

Oil is a fundamental input into the world economy because it is a primary source of energy in the industrial, electrical, and transport sectors. Hamilton (1983) argues that extreme oil price movements are partially responsible for the recessions that occurred between 1948 and 1972 in the United States. On the other hand, Sadorsky (1999) affirms that extreme movements in oil prices influence the economic activity and significantly affect movements in the stock market.

Therefore, under this environment of uncertainty and volatility, it is essential to have models that best describe fluctuations in oil prices in order to implement an efficient tool for managing the risk derived from extreme movements in oil prices. Value at Risk (VaR) has become the standard for measuring and evaluating risk in financial markets due to the

[1] OPEC controls approximately 43% of world oil production and 81% of oil reserves.

simplicity of its interpretation. VaR is defined as the maximum probable loss of a portfolio or financial instrument in a specified time horizon, for a given confidence level, under normal market circumstances, and as a consequence of adverse price movements.

The objective of this research is to estimate a GARCH-stable model to forecast oil price volatility and implement it in the VaR estimation. Additionally, Kupiec's statistical test analyzes the performance of the one-day VaR estimation considering GARCH models with alternative distributions to the stable in the innovation process such as the normal and generalized asymmetric Student t (GST) distributions.

It is critical to mention that in the VaR estimation the choice of the appropriate distribution of the innovation process is crucial since it directly impacts the quality of the estimation of the quantiles required to estimate the risk. Furthermore, the assumption on the distribution in the GARCH model is also significant in the VaR forecast, given that based on it the likelihood functions required to estimate the parameters are constructed and the future distribution of the risk is determined, which is conditioned to the predicted volatility.

The rest of the document contains the following: Section 2 reviews the literature on risk measurement in the oil sector, and section 3 describes the GARCH approach based on stable distribution and GST, the methodology of VaR estimates, and VaR performance tests. Section 5 describes the empirical results, and the document ends with the conclusions in section 6.

Review of the literature

Literature on risk measuring in the oil sector is currently scarce, despite the great need to manage the risk arising from oil price movements.

In order to provide a comparative view, this work summarizes the central studies in the literature, which demonstrate that GARCH models are widely used tools to analyze volatility and VaR in the oil sector.

Morana (2001) analyzes the applicability of the semi-parametric GARCH, proposed by Barone-Adesi *et al*. (1999), to forecast the distribution of Brent oil prices in short-term horizons. The results indicate that out-of-sample forecasts suggest that semi-parametric GARCH can be used to estimate VaR under different time horizons.

In the same line, Costello *et al*. (2008) analyze the performance of the historical simulation model with ARMA forecast (HSAF) and the semi-parametric GARCH model proposed by Barone-Adesi *et al*. (1999) in the Brent oil risk estimation. The findings indicate that the estimates of VaR using the semi-parametric model are higher than those obtained using the HSAF model.

In contrast, Cabedo and Moya (2003) propose the use of VaR in the quantification of risk in the Brent oil market. They estimate VaR using historical simulation (HS), historical

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simulation with ARMA forecasts (HSAF), and a parametric method based on GARCH under the normal hypothesis. The results indicate that the HSAF methodology provides a better estimation of VaR in percentage terms.

Similarly, Sadhegi and Shavvalpour (2006) compare the performance of the HSAF model and the parametric method based on the GARCH model under the normal hypothesis in the estimation of VaR using weekly prices of the OPEC mixture, unlike the previously mentioned researches. They conclude that the HSAF model is more efficient in estimating VaR.

On the other hand, Giot and Laurent (2003) evaluate the performance of the Risk Metrics method, and the APARCH[2] and ARCH models, both under the asymmetric Student t hypothesis in the estimation of the risk of Brent oil, WTI, aluminum, copper, nickel, and cocoa futures contracts. The results indicate that the APARCH model performs better in all cases; however, the ARCH model provides excellent results in VaR estimation, and its advantage is its smooth implementation.

For his part, Sadorsky (2006) analyzes the adjustment of different univariate and multivariate statistical models in the estimation of the volatility of the prices of WTI oil, heating oil #2, unleaded gasoline and natural gas, and compares the estimates of parametric and non-parametric VaR. The results indicate that in the case of oil futures, the GARCH model is the best fit in the estimation of volatility. However, considering the number of VaR surpluses, the nonparametric models surpass the parametric models.

Hung *et al*. (2008) compare the accuracy and efficiency of VaR estimates using the GARCH model under the normal hypothesis (GARCH-N), Student t (GARCH-t), and heavy tail distribution (GARCH-HT) for Brent oil, WTI, heating oil #2, propane, and NYHCGR gasoline. The findings indicate that VaR estimates based on GARCH-HT have better accuracy for both low and high confidence levels.

Fan *et al*. (2008) estimate VaR for Brent and WTI oil using the GARCH models under the Generalized Error Distribution (GARCH-GED) hypothesis, the Normal Hypothesis (GARCH-N), and using the HSAF model, and compare their respective efficiency. They conclude that the estimation of VaR through GARCH-GED is the most efficient.

Marimoutou *et al*. (2009) estimate VaR by applying the Extreme Value Theory (EVT) conditionally and unconditionally, and they compare the performance of these models with historical simulation models, HSAF, and some parametric models based on GARCH estimation for Brent and WTI oil. The results indicate that the conditional EVT and HSAF models have a higher performance than the rest of the compared models.

Aloui and Mabrouk (2010) compare the ability of some long memory GARCH models to predict the volatility of WTI and Brent oil prices, and NYHCGR and RCGR gasoline

[2] Asymmetric power autoregressive conditional heteroscedasticity model

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prices. Furthermore, they evaluate the performance of parametric VaR by considering three distributions: normal, Student t, and asymmetric Student t. They conclude that the FIGARCH model under the asymmetric Student t hypothesis shows a better performance in predicting VaR than the rest of the compared models.

Cheng and Hung (2011) estimate the conditional parametric VaR considering the generalized asymmetric Student t-distribution (GST), the Generalized Error Distribution (GED), and the normal distribution; the sample includes the daily prices of WTI oil, NYHCGR gasoline, heating oil #2, gold, silver, and copper. Conditional and unconditional coverage tests indicate that the estimation of VaR under the generalized asymmetric Student t hypothesis shows a better performance.

Youssef *et al*. (2015) compare the ability of some long memory GARCH models to predict the volatility of some energy prices including WTI and Brent oil and then apply them to VaR estimation by implementing Extreme Value Theory. They conclude that VaR estimates under the FIAPARCH-EVT method are the most accurate.

De Jesús Gutiérrez *et al*. (2016) apply the Extreme Values Theory in the estimation of VaR and CVaR for the case of the Mexican oil mix (MME for its acronym in Spanish), considering some GARCH models, and compare these estimates with those obtained through HS and HSAF. Kupiec's statistical test evidences that the conditional EVT and HSAF models present the best performance in the estimation of the conditional VaR of the short and long positions in any confidence level, although their performance reduces significantly in the CVaR prediction.

Following the Mexican case, Ruiz-Porras and Anguiano Pita (2016) analyze the multivariate case and describe the volatilities and interrelations of Brent, WTI, and MME oil yields using 12 GARCH models. Among their findings is that the AR(1)-TGARCH(1,1) model under the multivariate Student t hypothesis generates a satisfactory fit for the yields within this family of models.

This research differs from previous literature by at least two points. First, to the knowledge of the authors, GARCH-stable models have not been implemented to predict oil price volatility. Until now, stable distribution has been applied in risk analysis in the stock market, but the empirical characteristics of the oil yield series such as heavy tails, asymmetry, and volatility cluster suggest that the GARCH-stable model is an adequate model to capture these empirical characteristics in an efficient manner. Secondly, the performance of the one-day VaR estimation using Kupiec's statistical test is analyzed considering GARCH models with alternative distributions to the stable one, such as the generalized asymmetric Student t and normal distributions[3].

[3] Cheng and Hung (2011) point out, based on conditional and unconditional hedging tests, that the estimation of VaR under the generalized asymmetric Student t hypothesis shows better performance in the energy market.

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Methodology

This section describes the methodology applied to analyze the risk of returns on Brent, WTI, and MME oils.

Value at Risk (VaR)

Jorion (2001) defines Value at Risk as the maximum expected loss in a given time horizon for a given confidence level.

Definition. *Given X, a continuous random variable defined over the sample space* Ω, *which represents the change in the value of the asset (yield). Assuming that* $X: \Omega \rightarrow \mathbb{R}$ *is defined over a fixed probability space* (Ω, A, P)*, then the Value at Risk of X at level 1-q is defined as the minimum of the upper dimensions for a confidence interval of (1-q) %, such that:*

$$P\{X \leq -VaR_{1-q}^{X}\} = q \quad (1)$$

This definition indicates that it is possible to obtain the VaR given the function of cumulative distribution of asset yields:

$$-VaR_{1-q}^{X} = F_X^{-1}(q) \quad (2)$$

where $F_X^{-1}(\cdot)$ is the inverse of the function of cumulative distribution of asset yields over a period. In other words, VaR is the q-quantile of F_X. Therefore, the essence of the VaR calculations is the estimation of the lower quantiles of the cumulative distribution function of asset returns, which in practice, is unknown.

VaR estimation methods suggest different ways of constructing this function. The most common are: the parametric method based on the assumption that a parametric distribution characterizes changes in the value of the portfolio; the historical simulation where it is not necessary to assume a specific distribution of yields, and instead the predictions of its behavior are inferred using the historical behavior of the data; and the Monte Carlo simulation in which approximations of the expected yield behavior of a portfolio or financial instrument are obtained through simulations that generate random trajectories of the yields of the portfolio or financial instrument, considering certain initial assumptions on the volatilities and correlations of the risk factors.

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In this work, the VaR estimation is carried out through Monte Carlo simulation, under the stable hypothesis, generalized asymmetric Student t, and normal Student t.

α-stable *distribution and Generalized Asymmetric Student t-distribution*

In risk management, it is essential to find a distribution that appropriately describes the financial data. Commonly financial returns are not adequately described by a normal distribution, as empirical results show that financial data are generally asymmetric and have heavy tails (Fama, 1965; Bollerslev, 1986; Bali and Theodossiou, 2007; Champagnat *et al*., 2013). However, this characteristic is not exclusive to financial assets; the energy yield series also share these characteristics (Giot and Laurent, 2003; Hang *et al*., 2007; Fan *et al*., 2008).

Currently, most studies estimating the volatility of oil yields do so under the Gaussian hypothesis (Sadeghu and Shavvalpour, 2006). The existing literature regarding the estimation of volatility in the energy sector applying alternative distributions to the normal distribution is very scarce (Giot and Laurent, 2003; Hang *et al*., 2007; Fan *et al*., 2008; Hung *et al*., 2008; Marimoutou *et al*., 2009; Aloui and Mabrouk, 2010; Cheng and Hung, 2011; Youssef *et al*., 2015).

This work presents two families of distributions: stable distribution and generalized asymmetric Student t-distribution (GST), which allow describing the characteristics of asymmetry and yield kurtosis in the oil sector.

Generalized asymmetric Student t-distribution

There are several parameterizations of the generalized asymmetric Student t-distribution proposed in previous researches. Due to its simplicity, this study follows the parameterization proposed by Hansen (1994), which suggests an alternative parametric approach to model the conditional density function of the normalized error. It consists of selecting a distribution that depends on a vector of parameters of few dimensions and allowing this vector to vary according to the conditional variables.

Definition. *The generalized asymmetric Student t-distribution (GST) is the generalization of the Student t-distribution, which considers asymmetry. The probability density function of the standard GST distribution is defined as:*

$$f(z;\eta,\lambda) = \begin{cases} bc\left(1+\dfrac{1}{\eta-2}\left(\dfrac{bz+a}{1-\lambda}\right)^2\right)^{-\frac{\eta+1}{2}} & z < -\dfrac{a}{b} \\ bc\left(1+\dfrac{1}{\eta-2}\left(\dfrac{bz+a}{1+\lambda}\right)^2\right)^{-\frac{\eta+1}{2}} & z \geq -\dfrac{a}{b} \end{cases}$$

where $2 < \eta < \infty$, $-1 < \lambda < 1$, $a = 4\lambda c\frac{\eta-2}{\eta-1}$, $b = \sqrt{1+3\lambda^2-a^2}$ and $c = \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta-2)}\Gamma\left(\frac{\eta}{2}\right)}$.

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Hansen (1994) demonstrates that this is an appropriate density function with a mean of 0 and a variance of 1. Parameter η controls the thickness of the tail, and λ controls asymmetry. When $\eta \to \infty$, the distribution is reduced to asymmetrical normal distribution; when $\lambda=0$, it is reduced to Student t-distribution.

If a random Z variable follows a standard GST distribution with parameters η and λ, it is denoted as $Z \sim GST(\eta, \lambda)$. If the random variable Z follows a non-standard GST distribution with mean μ and variance σ^2, it is denoted as $Z \sim GST(\mu, \sigma, \eta, \lambda)$.

α-stable distribution

The family of *α-stable* or simply stable distributions is a class of probability distributions that allow asymmetry and heavy tails. In 1920, French mathematician Paul Lévy characterized this class of distributions in his study of sums of identically distributed independent terms. Stable distributions do not have explicit analytical expressions for either the probability density function (PDF) or the cumulative distribution function (CDF); however, their characteristic function (CF) describes them.

Definition. *An α-stable random variable X is commonly described by its characteristic function (CF), which is defined as:*

$$\Phi_X(t;\alpha,\beta,\gamma,\delta) = E[exp(iXt) = \begin{cases} exp\left(-\gamma^\alpha |t|^\alpha \left[1 - i\beta sgn(t) tan\left(\frac{\pi\alpha}{2}\right)\right] + i\delta t\right), \alpha \neq 1 \\ exp\left(-\gamma |t| \left[1 + i\beta \frac{2}{\pi} sgn(t) ln|t|\right] + i\delta t\right), \alpha = 1 \end{cases}$$

where, $sgn(t) = \{1\ si\ t > 0, 0\ si\ t = 0, -1\ si\ t < 0\}$, *is the stability index or characteristic exponent that reflects the size of the tails of the distribution;* $-1 \leq \beta \leq 1$ *is the asymmetry parameter that indicates the symmetry of the distribution;* $\gamma \geq 0$ *is a scale parameter also called dispersion; and* $\delta \in \mathrm{R}$ *is the position parameter.*

If a random Z variable follows a stable distribution it is denoted as $Z \sim S(\alpha, \beta, \gamma, \delta)$; thus a standard *α-stable* random variable is denoted as $Z \sim S(\alpha, \beta, 1, 0)$.

GARCH models

Volatility is the primary variable on which economic and financial pricing and hedging models are developed, so making estimates with the correct specifications of conditional distribution is crucial to improving their efficiency. This work implements GARCH(1,1) under the stable hypothesis, GST, and normal to describe the volatility of oil yields. Sadors-

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ky (2006) states that the GARCH model (1.1) has an excellent performance in estimating volatility in the oil sector.

Stable GARCH(1,1) model

The stable distribution was used to describe the empirical characteristics of oil yields, such as heavy tails, asymmetry, and volatility clusters. Moreover, it was used to describe the innovation process in the GARCH(1,1) model. Because in the case of stable distribution not all moments are defined, the TS-GARCH model proposed by Taylor (1986) and Schwert (1989) was used, in which yields are modeled as follows:

$$\begin{aligned} R_t &= \delta_t + \varepsilon_t \\ \varepsilon_t &= \gamma_t z_t \\ |\gamma_t| &= a_0 + a_1|\varepsilon_{t-1}| + b_1|\gamma_{t-1}| \end{aligned} \tag{3}$$

where R_t is the series of yields of the action in time t; δ_t and γ_t are the position and conditional dispersion parameters, respectively; and z_t are standardized stable random variables identical and independently distributed, $z_t \sim S(\alpha, \beta, 1{,}0)\;\; 1 < \alpha < 2$.

The parameters are estimated by maximum likelihood, using the STABLE program described in Nolan (1997).

GARCH(1,1)-GST model

Similarly, the GST distribution was used on the GARCH model to describe the stylized facts characteristic of the oil yield series. The model is below:

$$\begin{aligned} R_t &= \mu_t + \varepsilon_t \\ \varepsilon_t &= \sigma_t z_t \\ \sigma_t^2 &= a_0 + a_1(\varepsilon_{t-1} - c)^2 + b_1\sigma_{t-1}^2 \end{aligned} \tag{4}$$

To estimate the parameters of the GARCH model, the maximum likelihood estimation (MLE) method was used, where the probability density function of z_t was approximated using the approach proposed by Hansen (1994).

Normal GARCH(1,1) model

In this model, share yields are modeled as follows:

$$\begin{aligned} R_t &= \mu_t + \varepsilon_t \\ \varepsilon_t &= \sigma_t z_t \\ \sigma_t^2 &= a_0 + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2 \end{aligned} \quad (5)$$

Evaluation of the VaR performance

In this research, the evaluation of VaR performance is done in terms of its probability of empirical coverage, using Kupiec's statistic (1995). This statistic is an unconditional test that counts the number of VaR violations over the entire period, estimating whether the expected proportion of violations is equal to the level of significance α.

Kupiec's statistical test for large samples is distributed as a Chi-square with a degree of freedom and is given by:

$$LR_{UC} = -2ln\left[\frac{\alpha^n(1-\alpha)^{T-n}}{p^n(1-p)^{T-n}}\right] \quad (6)$$

where T represents the size of the sample, n is the number of violations, and $p=n/T$ is the percentage of violations. The null hypothesis, H_0: $n/T = \alpha$, is rejected with a significance level of 1% if the value of Kupiec's statistical test exceeds or is equal to the critical value of a Chi-square distribution with a degree of freedom, i.e., $LRUC \geq 6.635$.

Data and preliminary analysis

This section describes the database, shows descriptive statistics, unit root tests, ARCH effects tests, and goodness-of-fit tests of the respective distributions. The figures, tables, and algebraic routines required in this research were programmed in MATLAB R2017a.

Description of data and statistical analysis

This paper uses the daily closing prices of West Texas Intermediate (WTI), North Sea (Brent), and the Mexican export oil blend (MME), the sample covers the period from January 2, 2013, to December 29, 2017, obtaining a total of 1275 observations and the reference currency is the U.S. dollar. The price series were obtained from Bloomberg in the case of the Mexican oil mixture, and from the Energy Information Administration (EIA) website in the case of WTI and Brent.

These three oil mixtures were selected because, in the case of Brent, its price is the benchmark in European markets; WTI is the most accepted world reference price of a barrel of oil; and MME is the benchmark in the Mexican market.

The sample period was selected for two reasons: first, to analyze the VaR performance under the different distribution functions considered in this work in periods of high volatility, and second, because there is no reference to the VaR measurement in this specific period for this type of crude oil under the stability hypothesis. Additionally, there was a severe plunge in crude oil prices during this period, which experienced the third largest semi-annual depreciation in the last 24 years. The World Bank (Global Economic Prospects January 2015) identified four reasons for the 2014-2015 fall in oil prices by pointing to the first three factors as dominant: 1) oversupply at a time of weakening demand, 2) change in OPEC objectives, 3) reduced concern regarding geopolitical supply disruptions, and 4) appreciation of the US dollar.

Logarithmic yields were estimated as follows: $R_t = 100\ln\left(\frac{P_t}{P_{t-1}}\right)$, where *Pt* is the price in day *t*. Figure 1 shows the graph of the behavior of the daily closing oil prices and their respective logarithmic yields. In this figure, it is possible to observe that the series of logarithmic yields show heteroscedasticity and volatility clusters.

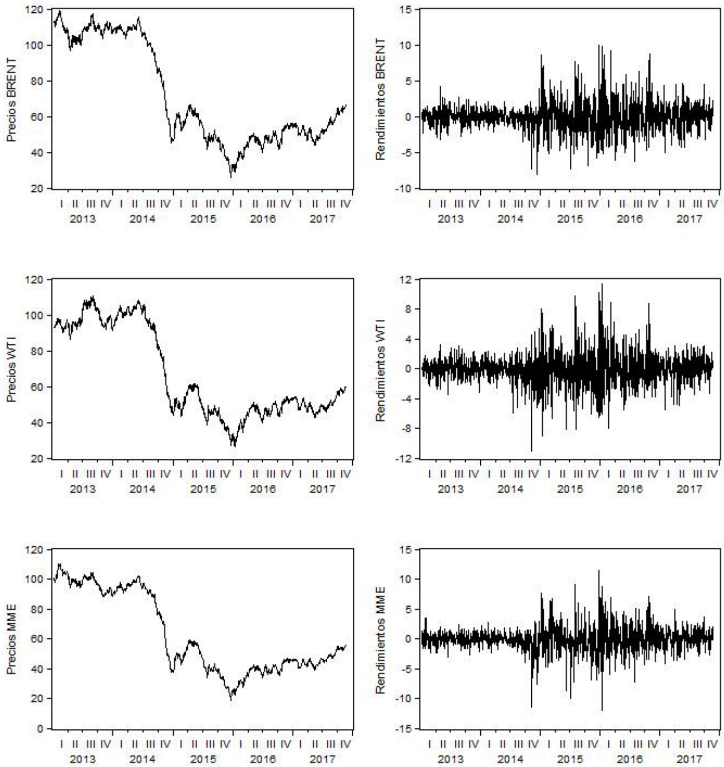

Figure 1. Daily prices and logarithmic yields

Source: own elaboration

Table 1 presents the descriptive statistics of the yields. Their normality is contrasted, and the unit root, stationarity; and ARCH effects tests are presented. It is possible to observe that the means of the three yields are small, negative, and show similar values. Conversely, the corresponding standard deviation is high in comparison to the mean, and the kurtosis indicates a leptokurtic behavior of the series. The statisticians Jarque-Bera (1980), Shapiro-Wilks (1965), and Anderson-Darling reject the hypothesis of normality in the series, and the unit root tests ADF (Dickey-Fuller, 1979) and PP (Phillips-Perron, 1988) reject the unit root hypothesis for the time series studied, meaning that the series are stationary. Furthermore, the results of the KPSS test (Kwiatkowski, Phillips, Schmidt, and Shin, 1992) reveal that it is not possible to reject the null hypothesis of stationarity with a deterministic trend at a significant level of 1%, i.e., all series present stationarity in trend. Finally, the ARCH-LM test rejects the hypothesis of the non-existence of ARCH effects (Engle, 1982), i.e., the series of studied yields show ARCH effects.

Table 1
Descriptive statistics and normality, unit root, and stationarity tests

Series	BRENT	WTI	MME
Panel A: Descriptive Statistic			
Mean	-0.0413	-0.0339	-0.0449
St. Dev.	2.0057	2.2014	1.9964
Asymmetry	0.4222	0.2113	0.0150
Kurtosis	6.1537	6.2773	8.2532
Panel B: Normality tests			
Jarque-Bera	565.80* (0.0000)	579.64* (0.0000)	1464.96* (0.0000)
Shapiro-Wilks	6.2800*	6.7707*	8.7466*
	(1.6934e-10)	(6.4069e-12)	(0.0000)
Anderson-Darling	4.7404*	2.8404*	9.0263*
	(5.0000e-04)	(5.0000e-04)	(5.0000e-04)
Panel C: Unit root and stationarity tests			
ADF	-34.1951* (0.0000)	-37.7924* (0.0000)	-30.6914* (0.0000)

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PP	-34.2847* (0.0000)	-37.7934* (0.0000)	-30.9370* (0.0000)
KPSS	0.2614	0.2113	0.2422
Panel D: ARCH effects test			
ARCH-LM	12.4524* (0.0000)	11.1306* (0.0000)	6.1016* (0.0000)

The ADF and PP unit root tests include a linear trend and intercept. The ARCH effects test is performed considering 5 lags. The p-values are shown in parentheses and * indicates significance at a level of 1%.

Source: own elaboration

Goodness of fit tests

In order to compare the goodness of fit of the alternative distributions considered in this document the Kolmogorov-Smirnov (KS) test is considered, the null hypothesis of which is H0: The data analyzed follow the distribution indicated. The null hypothesis is not rejected if the p-value exceeds or is equal to the chosen level of significance.

Table 2 shows the contrast statistic values of the KS test and its respective p-value, which indicate a non-rejection of the null hypothesis with a level of significance of α=.01, except for the MME series in the case of the GST distribution.

Table 2

Goodness of fit

Distributions	Stable	GST
	KS	KS
BRENT	0.0331 (0.1206)	0.0400 (0.0333)
WTI	0.0169 (0.8594)	0.0318 (0.1493)
MME	0.0395 (0.0365)	0.0529 (0.0015)

The p-values are shown between parentheses

Source: own elaboration

Estimation of the parameters of the probability distributions

The parameters of the alternative distributions considered were estimated by the maximum likelihood estimation (MLE) method. Table 3 shows the values obtained.

Table 3

Estimation of the parameters of the different alternative distributions

Distributions	Stable				GST	
Parameters	a	β	γ	δ	η	λ
BRENT	1.8396	0.0000	0.6549	-0.0161	6.7822	-0.0378
WTI	1.8894	-0.3878	0.6542	0.0328	7.8907	-0.0644
MME	1.7618	-0.0748	0.6116	0.0031	5.0064	-0.0073

95% confidence intervals are shown in parentheses

Source: own elaboration

Empirical Results

Estimation of the GARCH models

To describe the empirical characteristics of oil yields such as heavy tails, asymmetry, and volatility clusters, the GARCH(1,1) model was implemented under the stable, GST, and normal hypothesis. MLE estimated the parameters of the GARCH models, which are significant at 1%. Table 4 displays these estimates.

Table 4

Estimation of the parameters of the GARCH models

Parameters	a_0	a_1	c	b_1
Stable				
BRENT	0.0258	0.0646	-	0.9352
WTI	0.0329	0.0746	-	0.9252
MME	0.0207	0.0488	-	0.9510
GST				
BRENT	0.0000	0.0337	0.5899	0.9632
WTI	0.0000	0.0460	0.8056	0.9470
MME	0.0000	0.0313	0.6217	0.9649
Normal				
BRENT	0.0093	0.0580	-	0.9419
WTI	0.0242	0.0619	-	0.9348

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MME	0.0070	0.0449	-	0.9549

The standard errors are shown between parentheses

Source: own elaboration

Table 5 displays the values of the ARCH effects test on the standardized residuals. The results show the absence of conditional heteroscedasticity in the series of standardized residuals for each of the respective GARCH models.

Table 5

ARCH-LM effects test for standardized residuals

Series	GARCH-stable	GARCH-GST	GARCH-normal
BRENT	0.7391	0.7242	0.7637
WTI	0.0881	0.1019	0.0696
MME	0.4056	0.4028	0.4077

ARCH-LM is the test of ARCH effects (Engle, 1982) considering 5 lags

The p-values are shown in parentheses

Source: own elaboration

It is concluded from Tables 4 and 5 that the GARCH models analyzed adequately describe the clusters of conditional volatility, an empirical characteristic of oil yields, in addition to the fact that parameters a_1 and b_1 satisfy the condition of seasonality and indicate a high degree of persistence of volatility in yields.

VaR estimations

As previously mentioned, in the VaR estimation, the choice of the appropriate distribution of the innovation process is crucial since it directly impacts the quality of the estimation of the quantiles required to estimate the risk. Besides, the assumption on the distribution in the GARCH model is also fundamental in the VaR forecast, since the required likelihood functions to estimate the parameters are constructed based on this assumption and the future distribution of the risk is determined conditioned to the predicted volatility.

This document estimates one-day VaR by considering three alternative distributions in the innovation process: stable, generalized asymmetric Student t, and normal. Table 6 shows that the estimates of VaR-stable are higher than the estimates of VaR-normal and VaR-GST. It is also important to note that the estimates of VaR-normal at 95% confidence are higher than those of VaR-GST, whereas at 99% confidence these estimations show an opposite behavior.

Table 6

VaR estimations

Series	VaR 95%			VaR 99%		
	Stable	Normal	GST	Stable	Normal	GST
BRENT	-2.2459	-1.5061	-1.4040	-3.8157	-2.1530	-2.2040
WTI	-2.0262	-1.2554	-1.1841	-3.0884	-1.7685	-1.8482
MME	-1.8504	-1.1396	-1.0220	-3.3294	-1.6580	-1.7106

Source: own elaboration

Evaluation of VaR performance

The evaluation of VaR predictive performance under GARCH-stable, GARCH-GST, and GARCH-normal out-of-sample models is performed using historical data from the last year of the sample to predict the current VaR. Table 7 shows the results of Kupiec's statistical test, whose null hypothesis, H_0: $n/T = \alpha$, is rejected with a level of significance of α=1% if the value of the statistic exceeds or is equal to the critical value of a Chi-square distribution with a degree of freedom, that is, $LRUC \geq 6.635$. Values in bold indicate the model with the best performance for estimating VaR according to Kupiec's statistical test.

Table 7

Kupiec's statistical test

	Stable	Normal	GST
BRENT			
0.05	0.1044 (0.747)	13.017 (0.000)	19.095 (0.000)
0.01	5.0051 (0.025)	10.734 (0.001)	1.1644 (0.281)
WTI			
0.05	1.9772 (0.160)	22.404 (0.000)	22.404 (0.000)
0.01	1.1644 (0.281)	4.3148 (0.038)	1.9772 (0.160)
MME			
0.05	1.1644 (0.281)	22.404 (0.000)	25.876 (0.000)
0.01	5.0051 (0.025)	8.1149 (0.004)	1.1644 (0.281)

The p-values are shown between parentheses

Source: own elaboration

Table 7 presents the following results:

1. Normal distribution, as expected, shows poor performance in estimating VaR at both confidence levels, since the oil yields studied have an empirical distribution with

heavier than normal tails.

2. According to Kupiec's statistical test, the GST distribution shows poor performance in estimating VaR at 95% confidence. However, it shows excellent results at 99% confidence.
3. The stable distribution presents an excellent performance in the prediction of VaR since the empirical failure rates are statistically equal to their theoretical values.

Conclusions

In the oil sector, VaR has been implemented to quantify, as best as possible, the extreme movements in oil prices associated with a given level of confidence. This quantification is fundamental not only in the risk management of this sector but also in the economic and financial sector. Sadorsky (1999) states that extreme movements in oil prices influence economic activity, and significantly affect movements in the stock market.

For this purpose, in this research, VaR was quantified considering three types of oil (Brent, WTI and MME), and the performance of the one-day VaR estimation was analyzed using Kupiec's statistical test considering GARCH models with three alternative distributions in the innovation process: stable, generalized asymmetric Student t, and normal in a period of high volatility. The results obtained indicate that, at a confidence level of 99%, the VaR-stable and VaR-GST present an excellent performance in the prediction of VaR since the empirical failure rates are statistically equal to their theoretical values.

However, the results of the performance evaluation of the model based on Kupiec's statistical test indicate that the VaR-stable model is a more robust and accurate model for both confidence levels than those based on the GST and normal distribution. This result is crucial in the financial sector because it directly impacts the provisioning of reserves needed to address potential losses. In global terms, this is important for any agent in the international financial sector, as these reserves are a function of the level of risk faced by financial agents when they comprise a portfolio.

It is significant to mention that it would be possible to extend this research in the future by quantifying the risk in the oil market employing a stable multivariate model to analyze the potential interrelations between the volatilities of the different types of oil.

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