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Examining the Value-at-risk Performance of Fractionally Integrated GARCH Models: Evidence from Energy Commodities

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ABSTRACT

This study examines the out-of-sample value-at-risk forecasting performance of the generalised autoregressive conditional heteroscedasticity (GARCH), fractionally integrated GARCH (FIGARCH), hyperbolic GARCH (HYGARCH) and fractionally integrated, asymmetric power ARCH (FIAPARCH) models for West Texas intermediate crude oil, Europe Brent crude oil, heating oil#2, propane and New York Harbour Conventional Gasoline regular under the standard normal, student's t and skewed student's t distribution assumptions. Additionally, the expected shortfall is calculated in all cases. The results clearly show that the HYGARCH model under the normal distribution is the most accurate for short trading positions, whereas the FIGARCH model under the student's t distribution is preferred for long trading positions. This further implies that it is important to consider downside and upside risk separately to obtain more accurate results.

Keywords: Fractionally Integrated Generalised Autoraegressive Conditional Heteroscedasticity Models, Value-at-risk, Expected Shortfall, Energy Commodities

JEL Classifications: C58, C53, G31, Q40

1. INTRODUCTION

Since energy commodities are important industrial inputs, changes in energy prices can greatly impact the global economy (Sadorsky, 2006). Thus, volatility in the energy market concerns policymakers, financial institutions and manufacturers. Considering the past 15 years of commodity markets, we see that, especially after the 1999–2000 period, such developments as the increasing demand of emerging markets, growing financialisation and liberalisation of commodity markets, 2007–2008 global financial crisis, increased speculative trading and global liquidity levels and fluctuations in the U.S. dollar have caused significant changes in energy commodity prices (Arouri et al., 2013; Fan and Xu, 2011; Sadorsky, 2006). These changes, in turn, have further increased the volatility of energy commodities. In such an environment, accurate measurements of the market risk of energy commodities have become more important.

Value-at-risk (VaR) is the major tool used in both the literature and practice to measure a portfolio's market risk, defined as the maximum amount of loss to which a portfolio can be exposed due to market risk, with a given probability over a certain time horizon (Hendrics, 1996). Among various models of VaR, GARCH models are commonly used to measure the market risk of financial variables. GARCH models are able to successfully characterise the time series properties of financial data, such as heteroscedasticity, volatility clustering and time-varying conditional volatility (Bollerslev, 1986; Chkili et al., 2012). However, standard GARCH models have a key drawback: They suppose that volatility shocks decay at an exponential rate. In other words, they assume that the autocorrelation function of variance decreases quickly. Contrarily, however, the relevant literature reports that many financial assets, including energy commodities, exhibit volatility with long-memory properties. That is, a volatility shock in fact decays hyperbolically (Brunetti and Gilbert, 2000; Kang and Yoon, 2007; Kang and Yoon, 2013; Tabak and Cajueiro, 2007). Therefore, it may be appropriate to employ long-memory models, such as FIGARCH models, to better capture the stylised facts of financial time series.

In fact, the recent literature has reported increasing numbers of studies examining the performance of FIGARCH models, applying these long-memory models to a wide range of financial assets from stock indices (Kang and Yoon, 2007; Mabrouk and Saadi, 2012; Tang and Shieh, 2006) to agricultural commodities (Baillie et al., 2007; Jin and Frechette, 2004). Briefly, the relevant literature generally concludes that compared with standard GARCH-type models, models that take into account long memory, fat tails and asymmetry may perform better. Among alternative long-memory GARCH-type models, the FIAPARCH model with skewed Student's t distribution seems most appropriate choice (Aloui and Hamida, 2014; Aloui and Hamida, 2015; Arouri et al., 2012; Baillie et al., 2007; Bentes, 2015; Charfeddine, 2014; Degiannakis, 2004; Demiralay and Ulusoy, 2014; Kang et al., 2009; Charfeddine, 2016; Mabrouk and Saadi, 2012; Wei et al., 2010; Youssef et al., 2015). However, especially for energy commodities, the relevant literature has some limitations. For example, although the volatility of energy commodities has greatly increased in recent years, as Baillie et al. (2007), Aloui and Mabrouk (2010) and Chkili et al. (2014) point out, only a few studies have examined the VaR performance of different FIGARCH models for energy commodity markets. Additionally, such studies have not compared the out-of-sample VaR forecasting performance of alternative long-memory GARCH-type models such as FIGARCH, FIAPARCH and HYGARCH models for energy commodities under the assumptions of normal, Student's t and skewed student's t distributions.

In this regard, the main aim of this study is to examine the out-of-sample VaR forecasting performance of the FIGARCH, FIAPARCH and HYGARCH models, under the assumptions of normal, student's t and skewed student's t distributions, for energy commodities including West Texas intermediate crude oil (WTI), Europe Brent crude oil (Brent), heating oil#2, propane and gasoline. The standard GARCH model is also included to compare the performance of short- and long-memory models. We concentrate on these models' out-of-sample VaR forecasting performance because in-sample analysis can only demonstrate how a model has performed in the past; however, as commonly reported in the relevant literature, investors and financial institutions have greater need for a model that can forecast possible future losses (Tang and Shieh, 2006; Wang and Wu,2012).

This study contributes to the literature as follows. First, as mentioned above, only a few studies have examined the VaR performance of different FIGARCH models for energy commodity markets, despite such markets' increasing volatility. Second, although the relevant literature commonly reports that fat tails and asymmetry are important stylised facts of financial time series, including those for energy commodities, most cases of parametric VaR analysis consider only the standard normal and Student's t distribution assumptions, both of which are symmetric distributions (Fan et al., 2008). Therefore, this study additionally considers the skewed Student's t distribution to capture these stylised facts more accurately. Third, the expected shortfall (ES), another important part of financial risk management, is also calculated to present how much a risk manager will lose on average when the relevant VaR model fails (Giot and Laurent, 2003). Fourth, because investors can take both long and short positions in financial markets and because markets contain both producers and purchases of energy commodities, both upside and downside risks are considered (Aloui and Mabrouk, 2010; Fan et al., 2008). Fifth, as Aloui and Mabrouk (2010) and Poon and Granger (2003) point out, the backtesting procedure is one of the most important parts of VaR analysis. Therefore, to obtain robust results, both the unconditional coverage backtest proposed by Kupiec (1995) and the conditional coverage backtest introduced by Engle and Manganelli (2004) are employed in this study to evaluate the models' accuracies. Lastly, this study uses data covering the 2000–2015 period, capturing the various price phases experienced in the energy commodity markets[1]. This may further improve the performance of the models.

The rest of this paper is organised as follows. Section 2 outlines the data and methodology. Section 3 provides the empirical results, and Section 4 presents concluding remarks.

2. METHODOLOGY

The study uses the daily closing spot prices of WTI, Brent, heating oil#2, propane and New York Harbour Conventional Gasoline regular (gasoline) from 4 January 2000 to 4 August 2015, comprising nearly 3920 observations for each commodity. Following the relevant literature, the data set is divided into two sub-periods, with the last 1000 observations kept for the out-of-sample analysis. All daily prices are obtained from the U.S. Energy Information Administration. Continuously compounded daily returns (r_t) are calculated as follows:

$$r_t = 100^*[\ln(P_t) - \ln(P_{t-1})] \tag{1}$$

Where P_t is the closing price on day t.

2.1. GARCH-type Models

The standard GARCH (p,q) model developed by Bollerslev (1986) can be written as follows:

$$r_t = \mu + \varepsilon_t,\ \varepsilon_t = \sigma_t \epsilon_t,\ \epsilon_t \sim (0,1) \tag{2}$$

$$h_t = \omega_0 + \alpha_i \varepsilon_{t-1}^2 + \beta_j h_{t-1} \tag{3}$$

Where $\omega_0>0$, $\alpha_i>0$, $\beta_j>0$ and $\alpha_i+\beta_j<1$. Equations (2 and 3) show the conditional mean and variance, respectively.

However, as mentioned previously, one drawback of the standard GARCH model is its lack of long-memory properties, namely it assumes that a volatility shock decays exponentially. Alternatively, Baillie et al. (1996) propose the FIGARCH (1,d,1) model, which includes a slow decay of volatility (long memory) and is given by.

1 For example, from the beginning of 2000 until the second half of 2008, there was a sustainable increase in energy commodity prices that can be identified as a boom stage. However, a sharp decline in energy commodity prices was observed during the second half of 2008. Then, prices began to recover from the beginning of 2009 to the second half of 2011. Between the second half of 2011 and late 2014, energy commodities experienced stable price movements; however, a sharp price decline was then observed in the market, stabilising around 50 U.S. dollars to date.

$$h_t = \omega_0 + \beta h_{t-1} + \left[1-(1-\beta L)^{-1}(1-\phi L)(1-L)^d\right]\varepsilon_t^2 \quad (4)$$

Where $\omega_0>0$, $\beta<1$, $\phi<1$ and $0\leq d\leq 1$. L is the lag operator. d is the fractional integrater parameter. The FIGARCH model has the advantage that, for $0<d<1$, it flexibly allows an intermediate range of persistence. Thus, it nests the standard GARCH model when d=0 and nests the integrated GARCH (IGARCH) model when d=1.

Davidson (2004) propose another long-memory model, HYGARCH, which is a generalised form of the FIGARCH model. Davidson (2004) shows that this model allows the existence of second moments at more extreme amplitudes than do the simple IGARCH and FIGARCH models. The HYGARCH (1,d,1) model can be defined as follows:

$$h_t = \omega_0 + \left[1-(1-\beta L)^{-1}\phi L(1+\alpha((1-L)^d-1)\right]\varepsilon_t^2 \quad (5)$$

The HYGARCH model nests the FIGARCH model if a=1 and nests the GARCH model if a=0.

Although the FIGARCH and HYGARCH models include long-memory features, they do not cover asymmetry in volatility. To take this into account, Tse (1998) develops the FIAPARCH model, which considers both long memory and asymmetry in conditional variance. The FIAPARCH (1,d,1) model is written as.

$$h_t^{\delta} = \omega_0(1-\beta L)^{-1} + \left[1-(1-\beta L)^{-1}(1-\phi L)(1-L)^d\right](|\varepsilon_t| - \gamma\varepsilon_t)^d \quad (6)$$

Where $\omega_0>0$, $\delta>0$, $\phi<1$, $\beta<1$ and $-1<\gamma<1$. γ is the leverage coefficient. δ is the power term parameter. When $\gamma>0$ and is statistically significant, a negative shock affects conditional volatility more than would a positive shock of equal magnitude. However, when $\gamma=0$ and $\delta=2$, the FIAPARCH model nests the FIGARCH model.

2.2. Likelihood Functions

As mentioned before, all GARCH-type models are estimated under the assumptions of Gaussian normal, student's t and skewed student's t distributions. In this regard, if the return series has a Gaussian normal distribution, the log-likelihood function(L_{nrm}) is given by.

$$L_{nrm} = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2\right] \quad (7)$$

Where σ_t^2 is the variance, $z_t = \varepsilon_t / \sigma_t$ and T is the number of observations.

However, although the Gaussian normal distribution is commonly assumed because of its simplicity, it does not include the fat-tail phenomenon, which is a stylised fact of financial return series. Therefore, we also test the assumption of Student's t distribution. If a return series has Student's t distribution, the log-likelihood function (L_{st}) is written as follows:

$$L_{st} = T\left\{\ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln\left[\pi(\nu-2)\right]\right\} - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+\nu)\left[\ln(1+\frac{z_t^2}{\sigma_t^2(\nu-2)})\right]\right] \quad (8)$$

Where v is the degrees of freedom with v>2 and Γ(.) is the gamma function.

However, the student's t distribution is also symmetric, whereas financial return series are asymmetric. Therefore, the skewed student's t distribution proposed by Lambert and Laurent (2001) is also considered. If a return series has skewed student's t distribution, the log-likelihood function(L_{skwt}) is defined as follows:

$$L_{skwt} = T\left\{\ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln\left[\pi(\nu-2)\right] + \ln\left(\frac{2}{k+\left(1/k\right)}\right) + \ln(s)\right\} - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+\nu)\ln\left[1+\left(1+\frac{(sz_t+m)^2)}{\nu-2}\right)k^{-2I_t}\right]\right] \quad (9)$$

Where k is the asymmetry parameter.

2.3. Evaluating the VaR Forecasting Performance of Alternative GARCH-type Models

To determine the most accurate GARCH-type model, we calculate the out-of-sample 1-day-ahead VaR performance for the various alternative models. VaR is calculated for both long and short trading positions at significance levels ranging from 5% to 0.25%. Under the normal distribution assumption, the 1-day-ahead VaR values for long and short trading positions are calculated as follows:

$$VaR_{t(long)} = \mu_t - z_\alpha \sigma_t \;;\; VaR_{t(short)} = \mu_t - z_{1-\alpha}\sigma_t \quad (10)$$

Where μ_t is the mean conditional return, σ_t is the conditional standard deviation,z_α denotes the left a^{th} quantile and $z_{(1-\alpha)}$ is the right$(1-\alpha)^{th}$ quantile of the standard normal distribution.

Under the student's t distribution assumption, the 1-day-ahead VaR forecasts are calculated as follows:

$$VaR_{t(long)} = \mu_t - st_{\alpha,v}\sigma_t;\; VaR_{t(short)} = \mu_t - st_{-1-\alpha,v}\sigma_t \quad (11)$$

Where $st_{\alpha,v}$ is the left a^{th} quantile and $st_{1-\alpha,v}$ is the right $(1-\alpha)^{th}$ quantile of the student's t distribution with v degrees of freedom.

Under the skewed student's t distribution assumption, the 1-day-ahead VaR forecasts are calculated as follows:

$$VaR_{t(long)} = \mu_t - skwt_{\alpha,v}\sigma_t;\; VaR_{t(short)} = \mu_t - skwt_{1-\alpha,v}\sigma_t \quad (12)$$

Where $skwt_{\alpha,v}$ is the left a^{th} quantile and $skwt_{1-\alpha,v}$ is the right $(1-\alpha)^{th}$ quantile of the skewed student's t distribution with v degrees of freedom.

To measure the accuracy of the VaR forecasts of the alternative GARCH models, the Kupiec (1995) and dynamic quantile (DQ) tests developed by Engle and Manganelli (2004) are used. The Kupiec (1995) likelihood ratio unconditional coverage (LR_{uc}) test is defined as follows:

$$LR_{uc} = 2 * \ln[(1-f)^{T-N} f^{N}] - 2 * \ln[(1-\alpha)^{T-N} \alpha^{N}] \sim \chi^2_{(1)} \qquad (13)$$

Where T is the sample size, N is the number of exceptions[2], f is the exception rate (N/T)[3] and (1−α) is the confidence level. The LR_{uc} test measures whether the exception rate is statistically equal to the expected exception rate (α). In other words, the H_0: f = α null hypothesis is tested against the alternative H_1: f ≠ α hypothesis. If the null hypothesis can not be rejected, the relevant GARCH models' VaR forecasts are accurate. However, the LR_{uc} test ignores whether the exception rates are independently distributed. Therefore, Christofferson (1998) proposes a conditional coverage test to measure both whether exception rates are as expected and if they are randomly distributed. However, Christofferson's (1998) test considers only first-order dependency, ignoring possible higher-order dependency between exceptions. As an alternative conditional coverage test, Engle and Manganelli (2004) develop the (DQ) test, which is more powerful than Christofferson's (1998) test (Berkowitz et al., 2011) and is based on the following linear regression model:

$$Hit_t = \omega + \sum_{i=1}^{5} \vartheta_i Hit_{t-i} + \vartheta_{k+1} VaR_t + \eta_t \qquad (14)$$

Where variable $Hit_t(\alpha)$ is defined as $I(r_t < -VaR_\alpha) - \alpha$ and ϑ_i is the model parameter. The DQ test statistic is calculated as follows:

$$DQ = \frac{\vartheta^t X^t X \vartheta}{\alpha(1-\alpha)} \sim \chi^2_{(n+1)} \qquad (15)$$

Where X is the vector of the explanatory variables. The explanatory variables in Equation (14) consist of lagged values Hit_t from 1 to 5 and the contemporaneous VaR (VaR_t). n is the number of explanatory variables, six in this case. The null hypothesis is that the explanatory variables have no explanatory power at all, meaning that the exception rates are as expected and randomly distributed.

3. RESULTS

The descriptive statistics, unit root test results, ARCH results and long-memory test results for each energy commodity series are presented in Table 1. Panel A shows that all energy commodity return series, except that for propane, have positive mean values. Regarding the standard deviation, gasoline has the highest volatility, followed by propane. Additionally, all series are skewed, with excess kurtosis. Thus, the Jarque–Bera test rejects the null hypothesis of normal distribution. Panel B shows the results of Engle's (1982) ARCH test and the Ljung–Box Q statistics applied to the squared return series using 12 lags. Both tests indicate that the return series have strong ARCH effects. To examine whether the energy commodity return series are stationary, the augmented Dickey and Fuller (1979) unit root test, Phillips and Perron (1988) unit root test and Kwiatkowski et al., (1992) stationary test are used. The results show that all the series are stationary (Panel C). To analyse whether daily returns and volatility have long-memory characteristics, we employ the modified R/S test of Lo (1991) and the log- periodogram regression test of Geweke (1983) (GPH). The absolute and squared returns are used as proxies for volatility. The results of the long-memory tests clearly indicate that the energy commodity series exhibit long-memory properties in their volatility but short-memory properties in their returns (Panel D), findings that are consistent with the studies of Aloui and Mabrouk (2010) and Chkili et al. (2014). Briefly, all of these findings indicate that energy commodity return series have a non-normal distribution, exhibiting volatility clustering, long memory and fat tails. Therefore, GARCH-type models should be used with the consideration of these stylised facts.

3.1. Estimation Results of GARCH-type Models

First, the standard GARCH model is estimated[4]. All conditional variance coefficients are significant at a 5% or better significance level for all cases. The sum of the ARCH and GARCH parameters is close to one, indicating a high degree of persistence in the conditional variance of all energy commodities. Table 2 provides the estimation results of the FIGARCH model. The fractional difference parameters d are statistically significant at a 5% or better significance level in all cases, taking values ranging from 0.336 to 0.956. Similarly, the HYGARCH model also indicates (Table 3) that the long-memory parameters d are significant in all cases, ranging from 0.146 to 0.967. In addition, in all cases, the hyperbolic parameters $Log(\tilde{\alpha})$ are not statistically significant at conventional significance levels, meaning that the GARCH components are covariance stationary. Consistent with the previous two models, the results of the FIAPARCH model estimation also indicate that the fractional difference parameters d, ranging from 0.226 to 0.982, are significant at a 5% significance level in all cases (Table 4). Additionally, the power terms δ are significant at a 5% significance level for all cases, with values ranging from 1.592 to 2.287.

Further, the asymmetry parameters γ are found to be positive for WTI, Brent and gasoline, whereas they are negative for HT and propane. However, these values are statistically significant at conventional levels only for WTI and Brent, which means that the leverage effects are shown for WTI and Brent. That is, for those two energy commodities, negative shocks have a greater impact on conditional volatility than do positive shocks of equal magnitude. As for the assumptions of the student's t and skewed student's t distributions, the estimated tail parameters (ν) are found to be statistically significant at a 10% or better significance level in all cases, indicating fat-tail phenomena. In addition, the asymmetric parameters (ζ) are found to be negative in all cases except for HT; notably, however, these parameters are statistically significant only

2 The exception rate is the number of times returns exceed (in absolute value) the forecasted VaR in the sample.

3 The exception rate can also be defined as the failure rate. In this regard, 1−f corresponds to the success rate. Since, in this paper, quantiles ranging from 0.95 to 0.9975 are used for short trading positions, success rates are reported in the tables where VaR results are presented.

4 For simplicity, the results are not presented here but are available upon request. Hereafter, the nrm, st and skw t symbols are used for the standard normal, Student's t and skewed Student's t distributions, respectively.

Table 1: Statistics, unit root test results and long-memory test results for the return series

	WTI	Gasoline	Heating oil	Propane	Brent
Panel A: Summary statistics (%)					
Mean	0.0148	0.0252	0.0184	−0.0030	0.0181
Median	0.0857	0.0476	0.0000	0.0000	0.0422
Maximum	16.414	23.505	22.954	17.673	18.129
Minimum	−17.092	−17.889	−47.012	−49.912	−19.891
SD	2.4501	2.7493	2.6113	2.6236	2.2370
Skewness	−0.2512	0.0425	−1.6745	−2.7103	−0.2598
Kurtosis	7.7248	7.4329	45.756	54.7674	8.8075
Jargue-Bera	3680.94*	3205.05*	299881.1*	440929.1*	5602.4*
Panel B: ARCH effects tests					
Q2 (12)	1220.2*	1239.7*	1748.9*	155.00*	501.630*
ARCH (12)	44.424*	70.762*	131.262*	10.024*	22.564*
Panel C: Unit root tests					
ADF	−64.6050*	−60.9658*	−63.4844*	−40.8435*	−61.8202*
PP	−64.6525*	−60.9459*	−63.5972*	−60.1718*	−61.8327*
KPSS	0.1942	0.08820	0.1699	0.245314	0.20590
Panel D: long memory tests					
GPH test					
Return					
$m=T^{0.5}$	0.1099 (0.223)	−0.0558 (0.536)	0.0947 (0.297)	−0.0934 (0.305)	0.0578 (0.521)
$m=T^{0.6}$	0.0847 (0.138)	0.0886 (0.120)	−0.0127 (0.824)	0.0783 (0.170)	0.0527 (0.354)
$m=T^{0.7}$	−0.0302 (0.412)	−0.0164 (0.656)	0.0046 (0.898)	0.0101 (0.783)	0.0243 (0.507)
$m=T^{0.8}$	0.0345 (0.154)	−0.0217 (0.370)	−0.0268 (0.267)	−0.0076 (0.750)	0.0406 (0.092)
Squared return					
m=T0.5	0.6334*(0.000)	0.2759*(0.002)	0.0572 (0.525)	0.0902 (0.321)	0.7075*(0.000)
m=T0.6	0.4365*(0.000)	0.1934*(0.000)	0.1135*(0.046)	0.1449*(0.011)	0.3488*(0.000)
m=T0.7	0.2907*(0.000)	0.1979*(0.000)	0.2856*(0.000)	0.1215*(0.001)	0.2001*(0.000)
m=T0.8	0.2625*(0.000)	0.3175*(0.000)	0.4059*(0.000)	0.1324*(0.000)	0.1956*(0.000)
Absolute return					
$m=T^{0.5}$	0.7079*(0.000)	0.5920*(0.000)	0.2699*(0.003)	0.3560*(0.000)	0.676*(0.000)
$m=T^{0.6}$	0.4970*(0.000)	0.4096*(0.000)	0.2818*(0.000)	0.3737*(0.000)	0.4280*(0.000)
$m=T^{0.7}$	0.3415*(0.000)	0.3097*(0.000)	0.3863*(0.000)	0.3579*(0.000)	0.2989*(0.000)
$m=T^{0.8}$	0.2715*(0.000)	0.2543*(0.000)	0.3842*(0.000)	0.3160*(0.000)	0.2244*(0.000)
Lo's (1991) R/S test					
Return					
q=1	1.2404	0.9798	1.1504	1.2267	1.3098
q=2	1.2556	0.9774	1.1449	1.1962	1.2998
q=5	1.2552	0.9959	1.1694	1.1812	1.2855
Squared return					
q=1	3.8504*	4.0856*	2.0345*	2.1939*	3.9223*
q=2	3.5867*	3.7503*	2.1976*	2.1167*	3.7620*
q=5	3.0285*	3.1746*	1.6763	1.9425*	3.2923*
Absolute return					
q=1	5.5656*	6.4115*	5.9794*	4.0204*	5.0167*
q=2	5.1404*	5.9935*	5.3979*	3.6611*	6.2412*
q=5	4.2939*	5.1257*	4.3689*	3.0580*	5.8780*

q denotes the lag parameters used for Lo's (1991) R/S test. m denotes the bandwidth for the GPH test. *Denotes the 5% significance level. The ARCH (12) statistic is Engle's (1982) ARCH test applied to the squared return series using 12 lags under the null hypothesis of "no ARCH effect." Q^2 (12) are the Ljung–Box Q-statistics applied to the squared return series using 12 lags under the null hypothesis of "no ARCH effect." Figures in parentheses for the GPH test are the probability values. Both GPH and Lo's (1991) R/S test have the null hypothesis of no long memory. SD: Standard deviation

for WTI, Brent and gasoline, implying that those respective return series are skewed to the left.

As diagnostic checks, we use Tse's (2002) residual-based diagnostics (RBD) test, Engle's (1982) ARCH test and Ljung–Box Q statistics using 12 lags. Except for gasoline and HT, at least two test statistics in each case provide evidence that all models are capable of capturing the ARCH effects for all energy commodities at the 5% and/or 1% significance levels. However, the results are mixed for gasoline and HT because, for example, while the RBD test indicates that all models succeeded in capturing the ARCH effect for gasoline, the other two tests indicate that the standard GARCH model under all three distribution assumptions and the FIAPARCH model under the Student's t and skewed Student's t distribution assumptions can not eliminate the ARCH effect at conventional significance levels. However, as is well known, the general approach in the relevant literature is based on the principle that models should be selected according to their forecasting performance rather than their goodness-of-in-sample-fit.

Table 2: Results of the FIGARCH model estimation

Model	WTI	Gasoline	Heating oil	Propane	Brent
FIGARCH-nrm					
μ (mean)	0.0559**	0.0477	0.0469	0.0743*	0.0386
ω_0 (variance)	0.1123	0.2979*	0.0917*	0.2170**	0.1210**
d (long memory)	0.4249*	0.3395*	0.5363*	0.7182**	0.4339*
φ_1 (ARCH)	0.4417*	0.2781*	0.3065*	0.1740	0.1586**
β_1 (GARCH)	0.7206*	0.5145*	0.7045*	0.6743*	0.5714*
LL	−8594.94	−9152.51	−8616.27	−8352.494	−8366.56
AIC	4.3956	4.6806	4.3554	4.2793	4.2334
Q^2 (12)	0.2420	0.0935	0.2910	0.9991	0.2581
ARCH (12)	0.3575	0.1961	0.2868	0.9999	0.4024
RBD (12)	0.5889	1.0000	0.5844	0.9989	0.3278
FIGARCH – st					
μ (mean)	0.0739*	0.0728*	0.0380	0.0867*	0.0514**
ω_0 (variance)	0.0806*	0.2701*	0.1051*	0.2054*	0.0998*
d (long memory)	0.4511*	0.3371*	0.4074*	0.9565*	0.4069*
φ_1 (ARCH)	0.3996*	0.2702*	0.3213*	0.0546	0.2406*
β_1 (GARCH)	0.7344*	0.5253*	0.6138*	0.7922*	0.6232*
v (tail)	7.0562*	8.8520*	8.5228*	3.8289*	7.2054*
LL	−8494.64	−9103.21	−8449.602	−8085.78	−8282.51
AIC	4.34482	4.6558	4.3218	4.1432	4.1914
Q^2 (12)	0.0909	0.0034*	0.0870	0.9992	0.1863
ARCH (12)	0.1601	0.0126*	0.0978	0.9999	0.2500
RBD (12)	1.0000	1.0000	0.0000*	0.9930	0.9614
FIGARCH-skw t					
μ (mean)	0.0482	0.0538	0.0421	0.0828*	0.0278
ω_0 (variance)	0.0787*	0.2660*	0.1058*	0.2059*	0.0922*
d (long memory)	0.4502*	0.3358*	0.4087*	0.9555*	0.4086*
φ_1 (ARCH)	0.3924*	0.2723*	0.3203*	0.0552	0.2428*
β_1 (GARCH)	0.7296*	0.5258*	0.6141*	0.7916*	0.6290*
v (tail)	7.2033*	8.9122*	8.4709*	3.8292*	7.3795*
ζ (asymmetry)	−0.0700*	−0.0564*	0.0146	−0.0048	−0.0639*
LL	−8489.87	−9100.026	−8449.40	−8085.76	−8278.21
AIC	4.3428	4.6548	4.3222	4.1437	4.1897
Q^2 (12)	0.0889	0.0034*	0.0872	0.9992	0.1711
ARCH (12)	0.1581	0.0128*	0.0980	0.9999	0.2303
RBD (12)	0.9985	1.0000	0.0000*	0.9930	0.9547

*And**denote the 5% and 10% significance levels, respectively. The ARCH (12) statistic is Engle's (1982) ARCH test applied to the standardised residuals using 12 lags under the null hypothesis of "no ARCH effect." Q^2 (12) are the Ljung–Box Q statistics applied to the squared standardised residuals using 12 lags under the null hypothesis of "no ARCH effect" RBD (12) is Tse's (2002) residual-based diagnostic for conditional heteroscedasticity applied using 12 lags for the null hypothesis of "no ARCH effect." Figures for Q^2 (12), ARCH (12) and RBD (12) test statistics are the probability values. LL is the value of maximised log likelihood. AIC is the information criterion

3.2. Analysis of Out-of-sample VaR Forecasting

In this subsection, the out-of-sample 1-day-ahead VaR performance of the GARCH, FIGARCH, FIAPARCH and HYGARCH models is examined under the normal, student's t and skewed student's t distribution assumptions for each energy commodity return series. This out-of-sample analysis covers the past 4 years, comprising 1000 observations for each series. In the VaR calculations, quantiles ranging from 0.95 to 0.9975 are used for long trading positions and those from 0.05 to 0.0025 are used for short trading positions. GARCH models are re-estimated every 50 observations. Then, the forecasted 1-day-ahead VaR forecasts are compared with the observed returns; both results are recorded for later assessment using the Kupiec (1995) and DQ tests. The results are presented in Tables 5-9[5].

At the 5% significance level, regarding short trading positions, the LR_{uc} test results show that the HYGARCH-nrm and FIGARCH-nrm models are the most accurate. In all 25 cases, both models have seven rejections, while the HYGARCH-skw t model has eight rejections. At the 10% significance level, the HYGARCH-nrm model is the best, with 10 rejections, followed by the FIGARCH-nrm and FIAPARCH-nrm models, each with 12 rejections. At the 5% and 10% significance levels, the results of the DQ test show that the most accurate models are HYGARCH-nrm and HYGARCH-skw t, because each has the fewest rejections (six) at both significance levels. Taking these results together, the HYGARCH model with the assumption of normal distribution is clearly the most appropriate.

At the 5% significance level, regarding long trading positions, the results of the LR_{uc} test indicate that the FIGARCH-st, FIAPARCH-st and FIGARCH-skw t models are the most appropriate, with only one rejection each in all 25 cases. At the 10% significance level, the FIGARCH-st model alone is the best, with the fewest rejections (two). At the 5% and 10% significance levels, the results of the DQ test show that the FIGARCH-st,

5 For simplicity, the results of the GARCH model are not presented here but are available upon request.

Table 3: Results of the HYGARCH model estimation

Model	WTI	Gasoline	Heating oil	Propane	Brent
HYGARCH-nrm					
μ (mean)	0.0558**	0.0440	0.0470	0.0717*	0.0382
ω_0 (variance)	0.0953	0.0708	0.1119**	0.2586	0.0427
d (long memory)	0.4056*	0.1952*	0.5532*	0.8990*	0.3392*
φ_1 (ARCH)	0.4519*	0.2502	0.2950*	0.0877	0.1290
β_1 (GARCH)	0.7170*	0.3912*	0.7066*	0.7607*	0.4752*
Log($\tilde{\alpha}$) (hyperbolic)	0.0145	0.2345	−0.0136	−0.0409	0.0754
LL	−8594.81	−9149.38	−8515.95	−8347.25	−8364.34
AIC	4.3960	4.6795	4.3557	4.2771	4.2327
Q^2 (12)	0.2606	0.1535	0.2608	0.9989	0.2597
ARCH (12)	0.3801	0.2757	0.2649	0.9998	0.4312
RBD (12)	0.5925	0.8861	0.0026*	0.9997	0.4322
HYGARCH – st					
μ (mean)	0.0737*	0.0706*	0.0379	0.0862*	0.0495**
ω_0 (variance)	0.0572	−0.0346	0.1010**	0.2140*	0.0243
d (long memory)	0.4212*	0.1588*	0.4017*	0.9666*	0.3084*
φ_1 (ARCH)	0.4139*	0.2267	0.3229*	0.0484	0.2461*
β_1 (GARCH)	0.7267*	0.3676*	0.6109*	0.7954*	0.5602*
Log($\tilde{\alpha}$) (hyperbolic)	0.0200	0.3498	0.0041	−0.0176	0.0899
v (tail)	6.9597*	8.4714*	8.4938*	4.0228*	6.9050*
LL	−8494.436	−9099.09	−8449.59	−8085.14	−8280.54
AIC	4.3452	4.6543	4.3223	4.1434	4.1909
Q^2 (12)	0.1203	0.0077*	0.0864	0.9992	0.2208
ARCH (12)	0.2016	0.0221*	0.0966	0.9999	0.3062
RBD (12)	0.9998	0.9998	0.0000*	0.9992	0.6315
HYGARCH skw-t					
μ (mean)	0.0471	0.0476	0.0420	0.0813*	0.0227
ω_0 (variance)	0.0532	−0.0688	0.1025**	0.2151*	0.0079
d (long memory)	0.4182*	0.1457*	0.4044*	0.9656*	0.2994*
φ_1 (ARCH)	0.4073*	0.2202	0.3215*	0.0490	0.2492*
β_1 (GARCH)	0.7211*	0.3530*	0.6118*	0.7947*	0.5597*
Log($\tilde{\alpha}$) (hyperbolic)	0.0216	0.4015	0.0032	−0.0180	0.1018
v (tail)	7.0948*	8.5080*	8.4518*	4.0278*	7.0379*
ζ (asymmetry)	−0.0707*	−0.0632*	0.0145	−0.0065	−0.0687*
LL	−8489.63	−9095.275	−8449.39	−8085.09	−8275.76
AIC	4.3432	4.6528	4.3227	4.1439	4.1890
Q^2 (12)	0.1195	0.0081*	0.0868	0.9999	0.2084
ARCH (12)	0.2013	0.0229*	0.0971	0.9999	0.2915
RBD (12)	0.9774	0.9999	0.0000*	0.9993	0.5634

*And **denote the 5% and 10% significance levels, respectively. The ARCH (12) statistic is Engle's (1982) ARCH test applied to the standardised residuals using 12 lags under the null hypothesis of "no ARCH effect". Q^2 (12) are the Ljung–Box Q statistics applied to the squared standardised residuals using 12 lags under the null hypothesis of "no ARCH effect". RBD (12) is Tse's (2002) residual-based diagnostic for conditional heteroscedasticity applied using 12 lags for the null hypothesis of "no ARCH effect". Figures for Q^2 (12), ARCH (12) and RBD (12) test statistics are the probability values. LL is the value of maximised log likelihood. AIC is the information criterion

FIGARCH-skw t, HYGARCH-st and the HYGARCH-skw t models are the most accurate. Taking these results together, the FIGARCH-st model performs better than the others, although, notably, the results also indicate that the FIGARCH-skw t model performs rather closely to FIGARCH-st.

Additionally, the results also indicate that the worst models for short trading positions are the GARCH-st and GARCH-skw t models, followed by the FIGARCH-st, FIAPARCH-st and HYGARCH-st models. For long trading positions, by contrast, all long- and short-memory GARCH models under the assumption of normal distribution are found to have poor performance. Although the results suggest that the most accurate models for both long and short trading positions are long-memory GARCH-type models, long-memory GARCH models do not outperform short-memory GARCH models in all cases. For example, for short trading positions at both the 5% and the 10% significance levels, the results of the LR_{uc} test indicate that the GARCH-nrm model has better performance than the FIGARCH-st, FIAPARCH-st and HYGARCH-st models. Similarly, for long trading positions, at the two relevant significance levels, the results of the DQ test indicate that the GARCH-st and GARCH-skw t models outperform the FIGARCH-nrm, HYGARCH-nrm, FIAPARCH-nrm, FIAPARCH-st and FIAPARCH-skw t models.

Regarding the distribution assumptions, the results clearly indicate that the normal distribution performs the best for short trading positions, followed by the skewed Student's t and Student's t distributions. For example, at the 10% significance level based on the LR_{uc} test, the standard normal distribution has 34 rejections, while the skewed Student's t and Student's distributions have 43 and 47 respective rejections in all 75 cases. By contrast, for long trading positions, the findings indicate that both the student's t and the skewed Student's t distributions are the most appropriate

Table 4: Results of the FIAPARCH model estimation

Model	WTI	Gasoline	Heating oil	Propane	Brent
FIAPARCH-nrm					
μ (mean equation)	0.0295	0.0421	0.0475	0.0827*	0.0135
ω_0 (variance equation)	0.1178	0.2393	0.1235*	0.2393	−0.0627
d (long memory)	0.4032*	0.2939*	0.5408*	0.6604*	0.2261*
φ_1 (ARCH)	0.4734*	0.2686*	0.2941*	0.1857*	0.0158
β_1 (GARCH)	0.7256*	0.4636*	0.7012*	0.6468*	0.2093
γ (APARCH asymmetry)	0.2398*	0.0322	−0.0105	−0.0552	0.3738*
δ (APARCH power)	1.8224*	2.1719*	1.8273*	1.7596*	2.2002*
LL	−8584.30	−9151.67	−8514.40	−8345.59	−8335.94
AIC	4.3912	4.6811	4.3554	4.2768	4.2189
Q^2 (12)	0.2589	0.1194	0.1678	0.9974	0.1575
ARCH (12)	0.3824	0.2339	0.1823	0.9994	0.2767
RBD (12)	0.9999	0.9999	0.6757	0.9986	0.2135
FIAPARCH –st					
μ (mean equation)	0.0592*	0.0646**	0.0391	0.0873*	0.0426
ω_0 (variance equation)	0.0936**	0.1360	0.1406*	0.1398	−0.0087
d (long memory)	0.4065*	0.2600*	0.4437*	0.9822*	0.2472*
φ_1 (ARCH)	0.4263*	0.2505*	0.3129*	0.0515	0.2293**
β_1 (GARCH)	0.7167*	0.4357*	0.6416*	0.8307*	0.4419*
γ (APARCH asymmetry)	0.2899*	0.0946	−0.0026	−0.0077	0.3178*
δ (APARCH power)	1.7802*	2.2641*	1.8018*	1.5919*	2.1622*
v (tail)	7.2185*	8.5694*	8.8260*	4.0511*	7.5790*
LL	−8486.496	−9100.54	−8447.75	−8082.81	−8269.47
AIC	4.3416	4.6555	4.3218	4.1427	4.1858
Q^2 (12)	0.8103	0.0016*	0.0209*	0.9983	0.1472
ARCH (12)	0.2206	0.0058*	0.0315*	0.9996	0.2338
RBD (12)	0.9999	0.9999	0.9999	0.9992	0.3236
FIAPARCH skw-t					
μ (mean equation)	0.0301	0.0421	0.0433	0.0826*	0.0189
ω_0 (variance equation)	0.1002**	0.1144	0.1412*	0.1408	−0.0205
d (long memory)	0.4048*	0.2534*	0.4452*	0.9792*	0.2426*
φ_1 (ARCH)	0.4203*	0.2483*	0.3118*	0.0532	0.2240
β_1 (GARCH)	0.7116*	0.4277*	0.6421*	0.8294*	0.4344*
γ (APARCH asymmetry)	0.3206*	0.1068	−0.0042	−0.0087	0.3224*
δ (APARCH power)	1.7558*	2.2867*	1.8008*	1.5923*	2.1878*
v (tail)	7.4310*	8.5917*	8.7748	4.0536*	7.7905*
ζ(asymmetry)	−0.0799*	−0.0625*	0.0152	−0.0064	−0.0694*
LL	−8480.32	−9096.75	−8447.52	−8082.76	−8264.5
AIC	4.3390	4.6541	4.3223	4.1432	4.1838
Q^2 (12)	0.1272	0.0011*	0.0219*	0.9983	0.1449
ARCH (12)	0.2202	0.0042*	0.0331*	0.9997	0.2328
RBD (12)	0.9999	0.9999	0.9999	0.9991	0.3133

*And **denote the 5% and 10% significance levels, respectively. The ARCH (12) statistic is Engle's (1982) ARCH test applied to the standardised residuals using 12 lags under the null hypothesis of "no ARCH effect". Q^2 (12) are the Ljung–Box Q statistics applied to the squared standardised residuals using 12 lags under the null hypothesis of "no ARCH effect". RBD (12) is Tse's (2002) residual-based diagnostic for conditional heteroscedasticity applied using 12 lags for the null hypothesis of "no ARCH effect". Figures for Q^2 (12), ARCH (12) and RBD (12) test statistics are the probability values. LL is the value of maximised log likelihood. AIC is the information criterion

distribution assumptions, with the normal distribution showing the worst performance.

Moreover, the results also reveal that compared with short trading positions, the models are generally more successful in forecasting VaR for long trading positions. In other words, it seems that the models are better at capturing downside risk than upside risk. For example, considering the DQ test at the 10% significance level, while rejections range between 6 and 13 for short trading positions across different models, they range between 2 and 4 for long trading positions. The findings further reveal that models have quite different performance across long and short trading positions, meaning that downside and upside risk should be considered separately for more accurate results.

4. CONCLUSION

The increasing volatility of energy commodities has gained attention in both the literature and practice, with forecasting such volatility and measuring the market risk of energy commodities more accurately becoming important for financial institutions and investors. In this study, we examine the out-of-sample VaR forecasting performance of the FIGARCH, FIAPARCH and HYGARCH models under the assumptions of the normal, Student's t and skewed Student's t distributions for various energy commodities (WTI, Brent, heating oil#2, propane and gasoline). Additionally, we include the standard GARCH model to compare the performance of short- and long-memory models.

Table 5: Out-of-sample VaR forecasting performance and ES values of the models for WTI

Quantiles		Short trading position				Long trading position			
		1-f	LR_{uc}	DQ	ES	f	LR_{uc}	DQ	ES
FIGARCH-nrm									
0.9500	0.0500	0.9660	0.0140*	0.0889	3.945	0.0440	0.3745	0.3454	−4.193
0.9750	0.0250	0.9860	0.0152*	0.0423*	4.579	0.0300	0.3259	0.6407	−4.784
0.9900	0.0100	0.9970	0.0089*	0.0000*	8.135	0.0150	0.1389	0.8250	−5.271
0.9950	0.0050	0.9980	0.1258	0.6054	8.495	0.0100	0.0486*	0.8012	−5.789
0.9975	0.0025	0.9980	0.7428	0.9999	8.495	0.0080	0.0057*	0.6564	−6.054
FIGARCH-st									
0.9500	0.0500	0.9630	0.0484*	0.1309	3.923	0.0510	0.8850	0.4301	−4.049
0.9750	0.0250	0.9920	6.1E-05*	2.E-09*	5.499	0.0280	0.5509	0.5796	−4.802
0.9900	0.0100	0.9980	0.0019*	1.6E-05*	8.496	0.0130	0.3621	0.9509	−5.245
0.9950	0.0050	0.9990	0.0285*	0.0136*	9.001	0.0070	0.3979	0.9912	−6.471
0.9975	0.0025	0.9990	0.2795	0.8945	9.001	0.0040	0.3826	0.9956	−7.608
FIGARCH- skw t									
0.9500	0.0500	0.9620	0.0695	0.1531	3.906	0.0460	0.5565	0.4607	−4.115
0.9750	0.0250	0.9860	0.0152*	0.0423*	4.579	0.0270	0.6892	0.5736	−4.895
0.9900	0.0100	0.9980	0.0019*	1.6E-05*	8.4966	0.0090	0.7465	0.9973	−5.987
0.9950	0.0050	0.9980	0.1257	0.6054	8.496	0.0060	0.6638	0.9992	−6.971
0.9975	0.0025	0.9990	0.2795	0.8946	9.001	0.0040	0.3826	0.9956	−7.608
FIAPARCH-nrm									
0.9500	0.0500	0.9670	0.0087*	0.0203*	3.901	0.0430	0.2985	0.5915	−4.378
0.9750	0.0250	0.9860	0.0152*	0.0423*	4.542	0.0270	0.6892	0.4913	−4.904
0.9900	0.0100	0.9970	0.0089*	0.0000*	8.135	0.0160	0.0794	0.7246	−5.508
0.9950	0.0050	0.9980	0.1257	0.6054	8.496	0.0090	0.1071	0.8979	−5.987
0.9975	0.0025	0.9980	0.7428	0.9999	8.496	0.0080	0.0057*	0.6564	−6.054
FIAPARCH-st									
0.9500	0.0500	0.9670	0.0008*	0.0203*	4.015	0.0460	0.5565	0.6214	−4.313
0.9750	0.0250	0.9910	0.0002*	3.9E-07*	4.822	0.0230	0.6814	0.8440	−5.071
0.9900	0.0100	0.9980	0.0019*	1.6E-05*	8.496	0.0120	0.5377	0.9807	−5.856
0.9950	0.0050	0.9990	0.0285*	0.0136*	9.001	0.0060	0.6638	0.9992	−6.971
0.9975	0.0025	0.9990	0.2795	0.8946	9.001	0.0040	0.3826	0.9956	−7.608
FIAPARCH- skw t									
0.9500	0.0500	0.9620	0.0695	0.1467	3.849	0.0400	0.1333	0.2712	−4.451
0.9750	0.0250	0.9840	0.0512	0.2059	4.455	0.0210	0.4049	0.7815	−5.218
0.9900	0.0100	0.9970	0.0089*	0.0000*	8.135	0.0100	0.9999	0.9974	−6.293
0.9950	0.0050	0.9990	0.0285*	0.0136*	9.001	0.0040	0.6422	0.9993	−7.608
0.9975	0.0025	0.9990	0.2795	0.8946	9.001	0.0030	0.7589	0.9999	−8.417
HYGARCH-nrm									
0.9500	0.0500	0.9650	0.0217*	0.1280	3.887	0.0460	0.5565	0.4607	−4.109
0.9750	0.0250	0.9850	0.0288*	0.1051	4.421	0.0290	0.4293	0.5554	−4.813
0.9900	0.0100	0.9970	0.0089*	0.0000*	8.135	0.0160	0.0794	0.7246	−5.072
0.9950	0.0050	0.9980	0.1258	0.6054	8.496	0.0110	0.0203*	0.6819	−5.497
0.9975	0.0025	0.9980	0.7428	0.9999	8.496	0.0080	0.0057*	0.6564	−6.054
HYGARCH-st									
0.9500	0.0500	0.9640	0.0328*	0.0897	3.909	0.0520	0.7730	0.4578	−4.052
0.9750	0.0250	0.9890	0.0014*	0.0003*	4.867	0.0280	0.5509	0.5796	−4.802
0.9900	0.0100	0.9980	0.0019*	1.6E-05*	8.496	0.1200	0.5377	0.9807	−5.341
0.9950	0.0050	0.9990	0.0285*	0.0136*	9.001	0.0080	0.2162	0.9613	−6.054
0.9975	0.0025	0.9990	0.2795	0.8946	9.001	0.0040	0.3826	0.9956	−7.608
HYGARCH- skw t									
0.9500	0.0500	0.9620	0.0695	0.1531	3.927	0.0450	0.4608	0.4068	−4.156
0.9750	0.0250	0.9850	0.0288*	0.1051	4.421	0.0270	0.6892	0.5736	−4.895
0.9900	0.0100	0.9980	0.0019*	1.6E-05*	8.496	0.0100	1.0000	0.9974	−5.788
0.9950	0.0050	0.9980	0.1258	0.6054	8.496	0.0060	0.6638	0.9992	−6.971
0.9975	0.0025	0.9990	0.2795	0.8946	9.001	0.0040	0.3826	0.9956	-7.608

*Denotes the 5% significance level. Figures for LR_{uc} and LR_{cc} test statistics are probability values

Table 6: Out-of-sample VaR forecasting performance and ES values of the models for Brent

Quantiles		Short trading position				Long trading position			
		1-f	LR_{uc}	DQ	ES	f	LR_{uc}	DQ	ES
FIGARCH-nrm									
0.9500	0.0500	0.9770	1.3E-05*	7.9E-07*	3.860	0.0540	0.5664	0.8464	−3.289
0.9750	0.0250	0.9860	0.0152*	0.0430*	4.364	0.0320	0.1738	0.5440	−3.918
0.9900	0.0100	0.9950	0.0786	1.6E-08*	5.973	0.0160	0.0794	0.2066	−4.468
0.9950	0.0050	0.9980	0.1258	0.6054	6.343	0.0120	0.0078*	0.1055	−4.969
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0060	0.0607	0.8988	−5.979
FIGARCH-st									
0.9500	0.0500	0.9760	2.9E-05*	5.2E-06*	3.826	0.0580	0.2571	0.2465	−3.255
0.9750	0.0250	0.9880	0.0034*	0.0025*	4.615	0.0310	0.2411	0.5438	−4.013
0.9900	0.0100	0.9970	0.0089*	0.0116*	6.575	0.0120	0.5377	0.3526	−4.969
0.9950	0.0050	0.9990	0.0285*	0.0136*	8.508	0.0060	0.6638	0.9993	−5.979
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0040	0.3826	0.9958	−6.595
FIGARCH- skw t									
0.9500	0.0500	0.9690	0.0031*	0.0131*	3.550	0.0540	0.5665	0.3834	−3.323
0.9750	0.0250	0.9850	0.0288*	0.1063	4.234	0.0280	0.5509	0.7391	−4.120
0.9900	0.0100	0.9970	0.0089*	0.0116*	6.575	0.0090	0.7465	0.9978	−5.414
0.9950	0.0050	0.9990	0.0285*	0.0136*	8.508	0.0050	1.000	0.9999	−6.309
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0040	0.3826	0.9958	−6.596
FIAPARCH-nrm									
0.9500	0.0500	0.9790	2.2E-06*	8.02E-09*	3.919	0.0530	0.6663	0.9572	−3.288
0.9750	0.0250	0.9860	0.0152*	0.0001*	4.468	0.0350	0.0558	0.6214	−3.785
0.9900	0.0100	0.9950	0.0785	0.5239	5.078	0.0140	0.2306	0.9035	−4.645
0.9950	0.0050	0.9990	0.0285*	0.0136*	8.508	0.0070	0.3979	0.9920	−5.553
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0050	0.1639	0.9678	−6.242
FIAPARCH-st									
0.9500	0.0500	0.9790	2.2E-06*	8.0E-09*	3.919	0.0580	0.2571	0.7958	−3.274
0.9750	0.0250	0.9870	0.0075*	7.6E-06*	4.541	0.0290	0.4293	0.9517	−4.017
0.9900	0.0100	0.9980	0.0020*	1.6E-05*	7.773	0.0080	0.5102	0.9918	−5.504
0.9950	0.0050	0.9990	0.0285*	0.0136*	8.508	0.0040	0.6422	0.9994	−6.596
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0040	0.3826	0.9958	−6.596
FIAPARCH- skw t									
0.9500	0.0500	0.9740	0.0001*	0.0001*	3.699	0.0520	0.7731	0.8828	−3.345
0.9750	0.0250	0.9850	0.0288*	0.0008*	4.407	0.0250	1.000	0.9441	−4.134
0.9900	0.0100	0.9950	0.0786	0.5240	4.892	0.0080	0.5102	0.9918	−5.504
0.9950	0.0050	0.9980	0.1258	0.6054	7.773	0.0040	0.6422	0.9994	−6.596
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0040	0.3826	0.9958	−6.596
HYGARCH-nrm									
0.9500	0.0500	0.9750	6.4E-05*	2.6E-05*	3.681	0.0600	0.1590	0.5178	−3.183
0.9750	0.0250	0.9830	0.0857	0.0144*	4.170	0.0380	0.0143*	0.1822	−3.598
0.9900	0.0100	0.9930	0.3136	0.0017*	4.943	0.0190	0.0109*	0.3187	−4.103
0.9950	0.0050	0.9980	0.1258	0.6054	6.343	0.0140	0.0009*	0.1109	−4.614
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0070	0.0197*	0.7911	−5.601
HYGARCH-st									
0.9500	0.0500	0.9740	0.0001*	0.0001*	3.679	0.0650	0.0371*	0.1070	−3.134
0.9750	0.0250	0.9880	0.0034*	0.0025*	4.491	0.0330	0.1222	0.2205	−3.823
0.9900	0.0100	0.9970	0.0089*	0.0116*	6.575	0.0150	0.1389	0.4765	−4.532
0.9950	0.0050	0.9990	0.0285*	0.0136*	8.508	0.0070	0.3979	0.9920	−5.601
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0040	0.3826	0.9958	−6.596
HYGARCH- skw t									
0.9500	0.0500	0.9700	0.0018*	0.0065*	3.589	0.0590	0.2036	0.5204	−3.165
0.9750	0.0250	0.9830	0.0860	0.0144*	4.170	0.0310	0.2411	0.5438	−3.926
0.9900	0.0100	0.9950	0.0786	0.5239	4.892	0.0100	1.000	0.9979	−5.191
0.9950	0.0050	0.9980	0.1258	0.6054	6.343	0.0050	1.000	0.9999	−6.309
0.9975	0.0025	0.9990	0.2795	0.8946	8.508	0.0040	0.3826	0.9958	−6.596

*Denotes the 5% significance level. Figures for LR_{uc} and LR_{cc} test statistics are probability values

Table 7: Out-of-sample VaR forecasting performance and ES values of the models for gasoline

Quantiles		Short trading position				Long trading position			
		1-f	LR_{uc}	DQ	ES	f	LR_{uc}	DQ	ES
FIGARCH-nrm									
0.9500	0.0500	0.9770	1.3E-05*	6.7E-07*	5.311	0.0440	0.3746	0.8157	−4.353
0.9750	0.0250	0.9840	0.0512	0.0946	5.739	0.0260	0.8405	0.9297	−4.883
0.9900	0.0100	0.9900	1.000	0.9974	6.508	0.0150	0.1389	0.2311	−5.513
0.9950	0.0050	0.9940	0.6638	0.9992	6.812	0.0090	0.1071	0.8979	−5.747
0.9975	0.0025	0.9940	0.0607	0.8962	6.812	0.0060	0.0607	0.8962	−6.250
FIGARCH-st									
0.9500	0.0500	0.0470	5.4E-06*	7.2E-08*	5.426	0.0470	0.6603	0.9231	−4.246
0.9750	0.0250	0.0250	0.0288*	0.1098	5.779	0.0250	1.000	0.9230	−4.922
0.9900	0.0100	0.0120	0.5102	0.9909	6.612	0.0120	0.5377	0.3954	−5.856
0.9950	0.0050	0.0060	0.6638	0.9992	6.812	0.0060	0.6638	0.9992	−6.250
0.9975	0.0025	0.0020	0.7428	0.9999	8.554	0.0020	0.7428	0.9999	−6.468
FIGARCH- skw t									
0.9500	0.0500	0.9720	0.0005*	0.0002*	5.007	0.0440	0.3746	0.8157	−4.353
0.9750	0.0250	0.9840	0.0512	0.0946	5.739	0.0230	0.6814	0.8661	−5.004
0.9900	0.0100	0.9900	1.000	0.9974	6.508	0.0120	0.5377	0.3954	−5.856
0.9950	0.0050	0.9940	0.6638	0.9992	6.812	0.0050	1.000	0.9999	−6.366
0.9975	0.0025	0.9960	0.3826	0.9956	7.352	0.0020	0.7428	0.9999	−6.468
FIAPARCH-nrm									
0.9500	0.0500	0.9760	2.9E-05*	4.6E-06*	5.172	0.0450	0.4608	0.8394	−4.317
0.9750	0.0250	0.9840	0.0512	0.0946	5.739	0.0290	0.4293	0.8816	−4.660
0.9900	0.0100	0.9900	1.000	0.9974	6.508	0.0180	0.0223*	0.2652	−5.056
0.9950	0.0050	0.9930	0.3979	0.9912	6.684	0.0090	0.1071	0.8979	−5.747
0.9975	0.0025	0.9940	0.0607	0.8962	6.812	0.0080	0.0057*	0.6564	−5.750
FIAPARCH-st									
0.9500	0.0500	0.9720	0.0005*	0.0002*	4.886	0.7702	0.7702	0.8387	−4.191
0.9750	0.0250	0.9840	0.0512	0.0946	5.739	0.5509	0.5509	0.9070	−4.692
0.9900	0.0100	0.9920	0.5102	0.9908	6.644	0.2306	0.2305	0.8968	−5.274
0.9950	0.0050	0.9940	0.6638	0.9999	6.812	0.6638	0.6638	0.9992	−6.250
0.9975	0.0025	0.9960	0.3826	0.9956	7.352	0.3826	0.3826	0.9956	−6.634
FIAPARCH- skw t									
0.9500	0.0500	0.9660	0.0140*	0.0320*	4.531	0.0450	0.4608	0.8394	−4.317
0.9750	0.0250	0.9820	0.1359	0.2551	5.656	0.0250	1.000	0.9240	−4.777
0.9900	0.0100	0.9910	0.7465	0.9973	6.584	0.0100	1.000	0.9974	−6.004
0.9950	0.0050	0.9940	0.6638	0.9992	6.812	0.0060	0.6638	0.9992	−6.250
0.9975	0.0025	0.9960	0.3826	0.9956	7.352	0.0040	0.3826	0.9956	−6.634
HYGARCH-nrm									
0.9500	0.0500	0.9710	0.0001*	0.0035*	4.738	0.0520	0.7731	0.9338	−4.060
0.9750	0.0250	0.9830	0.0857	0.1928	5.618	0.0310	0.2411	0.7615	−4.567
0.9900	0.0100	0.9890	0.7544	0.9935	6.154	0.0190	0.0109*	0.2463	−4.977
0.9950	0.0050	0.9930	0.3979	0.9912	6.684	0.0130	0.0028*	0.4332	−5.050
0.9975	0.0025	0.9940	0.0607	0.8962	6.812	0.0080	0.0057*	0.6564	−5.750
HYGARCH-st									
0.9500	0.0500	0.9630	0.0484*	0.1778	4.402	0.0580	0.2571	0.6993	−3.938
0.9750	0.0250	0.9830	0.0857	0.1928	5.618	0.0340	0.0836	0.6914	−4.514
0.9900	0.0100	0.9900	1.000	0.9974	6.508	0.0170	0.0431*	0.4290	−5.032
0.9950	0.0050	0.9940	0.6638	0.9992	6.812	0.0090	0.1071	0.8979	−5.488
0.9975	0.0025	0.9960	0.3826	0.9956	7.352	0.0050	0.1639	0.9667	−6.366
HYGARCH- skw t									
0.9500	0.0500	0.9610	0.0974	0.1921	4.381	0.0550	0.4749	0.9192	−3.968
0.9750	0.0250	0.9810	0.2047	0.4664	5.383	0.0300	0.3259	0.8876	−4.560
0.9900	0.0100	0.9890	0.7544	0.9935	6.154	0.0160	0.0794	0.4701	−5.125
0.9950	0.0050	0.9940	0.6638	0.9992	6.812	0.0080	0.2162	0.9613	−5.750
0.9975	0.0025	0.9940	0.0607	0.8962	6.812	0.0040	0.3826	0.9956	−5.576

*Denotes the 5% significance level. Figures for LR_{uc} and LR_{cc} test statistics are probability values

Table 8: Out-of-sample VaR forecasting performance and ES values of the models for heating oil

Quantiles		Short trading position				Long trading position			
		1-f	LR_{uc}	DQ	ES	f	LR_{uc}	DQ	ES
FIGARCH-nrm									
0.9500	0.0500	0.9750	6.4E-05*	6.7E-05*	4.142	0.0480	0.7702	0.8648	−3.446
0.9750	0.0250	0.9840	0.0512	0.2094	4.996	0.0280	0.5509	0.5331	−3.965
0.9900	0.0100	0.9890	0.7544	0.9935	5.391	0.0140	0.2306	0.8968	−5.078
0.9950	0.0050	0.9930	0.3979	0.9912	5.695	0.0100	0.0486*	0.8012	−5.189
0.9975	0.0025	0.9940	0.0607	0.8962	5.929	0.0060	0.0607	0.8962	−6.599
FIGARCH-st									
0.9500	0.0500	0.9740	0.0001*	0.0002*	4.059	0.0490	0.8843	0.9225	−3.413
0.9750	0.0250	0.9840	0.0512	0.2094	4.996	0.0270	0.6892	0.4885	−4.013
0.9900	0.0100	0.9920	0.5102	0.9908	5.908	0.0120	0.5377	0.9807	−5.484
0.9950	0.0050	0.9940	0.6638	0.9992	5.929	0.0060	0.6638	0.9992	−6.599
0.9975	0.0025	0.9960	0.3826	0.9956	6.424	0.0060	0.3826	0.8962	−6.599
FIGARCH- skw t									
0.9500	0.0500	0.9750	6.4E-05*	6.7E-05*	4.142	0.0490	0.8843	0.9225	−3.413
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0270	0.6892	0.4885	−4.013
0.9900	0.0100	0.9920	0.5102	0.9908	5.908	0.0130	0.3621	0.9509	−5.279
0.9950	0.0050	0.9950	1.000	0.9999	6.289	0.0060	0.6638	0.9992	−6.599
0.9975	0.0025	0.9960	0.3826	0.9956	6.424	0.0060	0.0607	0.8962	−6.599
FIAPARCH-nrm									
0.9500	0.0500	0.9780	5.4E-06*	6.5E-07*	4.347	0.0440	0.3746	0.8958	−3.574
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0270	0.6892	0.4885	−4.076
0.9900	0.0100	0.9900	1.000	0.9974	5.668	0.0140	0.2306	0.8968	−5.078
0.9950	0.0050	0.9920	0.2163	0.9613	5.908	0.0070	0.3980	0.9912	−6.173
0.9975	0.0025	0.9950	0.1639	0.9667	6.289	0.0060	0.0607	0.8962	−6.599
FIAPARCH-st									
0.9500	0.0500	0.9780	5.4E-06*	6.5E-07*	4.347	0.0410	0.1783	0.5986	−3.721
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0250	1.000	0.8265	−4.174
0.9900	0.0100	0.9910	0.7465	0.9973	5.901	0.0080	0.5102	0.9908	−6.829
0.9950	0.0050	0.9950	1.000	0.9999	6.289	0.0060	0.6638	0.9992	−6.599
0.9975	0.0025	0.9970	0.7589	0.9999	7.556	0.0060	0.0607	0.8962	−6.599
FIAPARCH- skw t									
0.9500	0.0500	0.9780	5.4E-06*	6.5E-07*	4.347	0.0430	0.2985	0.6728	−3.641
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0250	1.000	0.8265	−4.174
0.9900	0.0100	0.9920	0.5102	0.9908	5.908	0.0090	0.7465	0.9973	−6.422
0.9950	0.0050	0.9950	1.000	0.9999	6.289	0.0060	0.6638	0.9992	−6.599
0.9975	0.0025	0.9970	0.7589	0.9999	7.556	0.0060	0.0607	0.8962	−6.599
HYGARCH-nrm									
0.9500	0.0500	0.9780	5.4E-06*	6.5E-07*	4.347	0.0410	0.1783	0.5986	−3.684
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0260	0.8405	0.8006	−4.046
0.9900	0.0100	0.9910	0.7465	0.9973	5.901	0.0130	0.3621	0.9509	−5.253
0.9950	0.0050	0.9930	0.3979	0.9912	5.695	0.0070	0.3979	0.9912	−6.173
0.9975	0.0025	0.9950	0.1639	0.9667	6.289	0.0060	0.0607	0.8962	−6.599
HYGARCH-st									
0.9500	0.0500	0.9780	5.4E-06*	6.5E-07*	4.347	0.0420	0.2332	0.6429	−3.649
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0240	0.8384	0.8375	−4.167
0.9900	0.0100	0.9920	0.5102	0.9908	5.908	0.0090	0.7465	0.9973	−6.359
0.9950	0.0050	0.9950	1.000	0.9999	6.289	0.0060	0.6638	0.9992	−6.599
0.9975	0.0025	0.9960	0.3826	0.9956	6.424	0.0060	0.0607	0.8962	−6.599
HYGARCH- skw t									
0.9500	0.0500	0.9790	2.2E-06*	8.7E-08*	4.414	0.0420	0.2332	0.6429	−3.649
0.9750	0.0250	0.9850	0.0288*	0.1078	5.173	0.0250	1.000	0.8265	−4.109
0.9900	0.0100	0.9920	0.5102	0.9908	5.908	0.0100	1.000	0.9974	−6.039
0.9950	0.0050	0.9950	1.000	0.9999	6.289	0.0060	0.6638	0.9992	−6.599
0.9975	0.0025	0.9960	0.3826	0.9956	6.424	0.0060	0.0607	0.8962	−6.599

*Denotes the 5% significance level. Figures for LR_{uc} and LR_{cc} test statistics are probability values

Table 9: Out-of-sample VaR forecasting performance and ES values of the models for propane

Quantiles		Short trading position				Long trading position			
		1-f	LR_{uc}	DQ	ES	f	LR_{uc}	DQ	ES
FIGARCH-nrm									
0.9500	0.0500	0.9607	0.1077	0.2204	4.571	0.0604	0.1439	0.4003	−5.352
0.9750	0.0250	0.9768	0.7073	0.8462	5.258	0.0373	0.0209*	0.3344	−6.154
0.9900	0.0100	0.9889	0.7373	0.9931	6.001	0.0211	0.0021*	0.0040*	−7.524
0.9950	0.0050	0.9929	0.3886	0.9905	6.709	0.0130	0.0026*	2.5E-05*	−7.744
0.9975	0.0025	0.9969	0.7502	0.9999	5.930	0.0091	0.0014*	0.0001*	−8.055
FIGARCH-st									
0.9500	0.0500	0.9577	0.2530	0.4996	4.730	0.0674	0.0162*	0.0800	−5.183
0.9750	0.0250	0.9848	0.0313*	0.1188	5.734	0.0342	0.0772	0.2728	−6.425
0.9900	0.0100	0.9949	0.0820	0.5416	7.960	0.0080	0.5241	0.0230*	−7.793
0.9950	0.0050	0.9989	0.0294*	0.0152*	6.296	0.0060	0.6521	0.9991	−7.445
0.9975	0.0025	1.000	0.0000*	0.0000*	-	0.0010	0.2838	0.8998	−11.23
FIGARCH- skw t									
0.9500	0.0500	0.9577	0.2530	0.4996	4.730	0.0674	0.0162*	0.0800	−5.183
0.9750	0.0250	0.9848	0.0313*	0.1188	5.734	0.0352	0.0512	0.2906	−6.365
0.9900	0.0100	0.9950	0.0821	0.5416	7.960	0.0081	0.5241	0.0230*	−7.793
0.9950	0.0050	0.9989	0.0295*	0.0152*	6.296	0.0060	0.6521	0.9991	−7.445
0.9975	0.0025	1.000	0.0000*	0.0000*	-	0.0010	0.2838	0.8999	−11.23
FIAPARCH-nrm									
0.9500	0.0500	0.9587	0.1946	0.2938	4.811	0.0604	0.1439	0.3950	−5.375
0.9750	0.0250	0.9778	0.5583	0.8099	5.360	0.0433	0.0008*	0.0078*	−6.185
0.9900	0.0100	0.9869	0.3499	0.9479	6.038	0.0211	0.0021*	0.0041*	−7.677
0.9950	0.0050	0.9919	0.2099	0.9594	6.651	0.0171	2.3E-05*	0.0005*	−8.403
0.9975	0.0025	0.9949	0.1601	0.9656	7.960	0.0111	7.1E-05*	3.9E-08*	−8.389
FIAPARCH-st									
0.9500	0.0500	0.9546	0.4918	0.2818	4.712	0.0695	0.0076*	0.0260*	−5.172
0.9750	0.0250	0.9818	0.1449	0.4933	5.925	0.0352	0.0512	0.2928	−6.758
0.9900	0.0100	0.9949	0.0820	0.5416	7.960	0.0121	0.5226	4.9E-06*	−8.462
0.9950	0.0050	0.9989	0.0295*	0.0152*	6.296	0.0070	0.3886	0.0032*	−7.678
0.9975	0.0025	1.000	0.0000*	0.0000*	-	0.0020	0.7509	0.9999	−9.073
FIAPARCH- skw t									
0.9500	0.0500	0.9547	0.4918	0.2818	4.712	0.0705	0.0051*	0.0270*	−5.157
0.9750	0.0250	0.9828	0.0920	0.3557	6.109	0.0363	0.0331*	0.2936	−6.643
0.9900	0.0100	0.9949	0.0821	0.5446	7.960	0.0121	0.5226	4.9E-06*	−8.462
0.9950	0.0050	0.9999	0.0294*	0.0152*	6.296	0.0070	0.3886	0.0031*	−7.678
0.9975	0.0025	1.000	0.0000*	0.0000*	-	0.0020	0.7509	0.9999	−9.072
HYGARCH-nrm									
0.9500	0.0500	0.9597	0.1464	0.2599	4.922	0.0614	0.1100	0.4688	−5.372
0.9750	0.0250	0.9778	0.5583	0.8099	5.360	0.0382	0.0129*	0.2950	−6.570
0.9900	0.0100	0.9879	0.5226	0.9794	5.953	0.0201	0.0048*	0.0025*	−7.921
0.9950	0.0050	0.9929	0.3886	0.9905	7.178	0.0161	8.3E-05*	0.0002*	−8.594
0.9975	0.0025	0.9949	0.1601	0.9656	7.960	0.0091	0.0014*	0.0001*	−8.055
HYGARCH-st									
0.9500	0.0500	0.9547	0.4912	0.6354	4.732	0.0695	0.0076*	0.0384*	−5.156
0.9750	0.0250	0.9849	0.0313*	0.1188	5.734	0.0373	0.0209*	0.2986	−6.687
0.9900	0.0100	0.9949	0.0820	0.5416	7.960	0.0091	0.7631	0.0883	−7.956
0.9950	0.0050	0.9990	0.0295*	0.0152*	6.296	0.0060	0.6521	0.9991	−7.445
0.9975	0.0025	1.000	0.0000*	0.0000*	-	0.0010	0.2838	0.8999	−11.23
HYGARCH- skw t									
0.9500	0.0500	0.9556	0.4020	0.5448	4.738	0.0705	0.0051*	0.0396*	−5.125
0.9750	0.0250	0.9849	0.0313*	0.1188	5.734	0.0383	0.0128*	0.2948	−6.581
0.9900	0.0100	0.9949	0.0820	0.5416	7.960	0.0091	0.7631	0.0883	−7.956
0.9950	0.0050	0.9989	0.0295*	0.0152*	6.296	0.0060	0.6521	0.9990	−7.445
0.9975	0.0025	1.000	0.0000*	0.0000*	-	0.0010	0.2838	0.8999	−11.23

The "-" symbol means that the relevant model produced no exceptions. However, it also implies that the relevant model's VaR performance is inadequate. Figures for LR_{uc} and LR_{cc} test statistics are probability values

The main findings are as follows. First, the results indicate that the FIAPARCH model with the skewed Student's t distribution is not the most appropriate model. Instead, the results show that accurately measuring upside market risk for the relevant energy commodities is best modelled by HYGARCH under the assumption of normal distribution, whereas downside market risk for the same commodities is best modelled by FIGARCH under the assumption of Student's t distribution. When analysing market risk, both traders taking short positions and purchasers of energy commodities should prefer the HYGARCH model under the assumption of normal distribution, while traders taking long positions and producers of energy commodities should consider the FIGARCH model under the assumption of Student's t distribution. Second, most relevant studies carry out downside risk analysis (e.g., Ane, 2006; Angelidis et al., 2004; Cifter, 2011; Degiannakis et al., 2013; Escanciano and Pei, 2012; Orhan and Köksal, 2012; So and Yu, 2006). In other words, papers have typically only examine the performance of alternative models for long trading positions, although such models are then proposed for use in both downside and upside VaR analysis. However, this study clearly shows that model performance can change significantly across long compared with short trading positions. Therefore, downside and upside risk must be considered separately for the most accurate results. Third, the results here reveal that the standard normal distribution is an appropriate assumption for analysing upside market risk, whereas both the Student's t and the skewed Student's t distributions should be used for measuring downside market risk. Fourth, the findings indicate that compared with their ability to model upside market risk, the models are more successful at measuring downside market risk. In this regard, the findings presented in this study make important contributions to the practices of market risk analysis, variance forecasting, option pricing, asset allocations and hedging decisions concerning energy commodities.

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