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Viewpoint

Energy risk management and value at risk modeling

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Abstract

The value of energy trades can change over time with market conditions and underlying price variables. The rise of competition and deregulation in energy markets has led to relatively free energy markets that are characterized by high price shifts. Within oil markets the volatile oil price environment after OPEC agreements in the 1970s requires a risk quantification.'' Value-at-risk'' has become an essential tool for this end when quantifying market risk. There are various methods for calculating value-at-risk. The methods we introduced in this paper are Historical Simulation ARMA Forecasting and Variance–Covariance based on GARCH modeling approaches. The results show that among various approaches the HSAF methodology presents more efficient results, so that if the level of confidence is 99%, the value-at-risk calculated through HSAF methodology is greater than actual price changes in almost 97.6 percent of the forecasting period.

Keywords: Energy price risk; Price risk management; Value-at-risk; HSAF methodology; Garch model

1. Introduction

Risk Management embodies the process and the tools used for evaluating, measuring and managing the various risks within a Company's portfolio of financial, commodity and other assets. The value of energy trades can change over time as market conditions and underlying price variables change. A price forecast is the foundation for determining a firm's risk in managing their energy supply and their forward contracts for energy trades.

In energy markets, proper risk management depends not only upon proper portfolio analysis tools but also on a solid foundation of forward price.

Calls for competition in the power and gas industry have made deregulation an attractive option around the world. The rise of competition and deregulation in turn has led to relatively free energy markets that are characterized by high price shifts. Within oil markets the volatile oil price environment after OPEC agreements in the 1970s requires risk quantification. Value-at-Risk has become an essential tool for this end, when quantifying market risk. Within oil markets, value-at-risk (VaR) can be used to quantify the maximum oil price changes associated with a likelihood level. This quantification constitutes a fundamental point when designing risk management strategies. This paper aims at addressing the importance of oil price risk in managing price risk in energy markets and introducing the application of VaR in quantifying oil price risk.

The rest of this paper is set as follows: in Section 2 we put forward the fundamental of managing price risk in energy markets and the importance of price volatility in managing energy risk. Section 3 introduces the VaR modelling procedure and analyzes the main methodologies and models that can be used to determine VaR. Section 4 is devoted to addressing the proposed methodology. The final two sections present the empirical analysis and the main conclusions of this paper, respectively.

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2. Price volatility and price risk management in energy markets

Risk management embodies measuring and managing the various risks within a company's portfolio of financial, commodity and other assets. Wengler (2001) argues that in the energy market, producers and providers enter into trading contracts that help match supply with demand. Energy firms buy or sell contracts on the open market to

- meet contracted deliveries when demand exceeds production capacity,
- sell excess capacity when demand is less than supply, and
- speculate to increase earnings through futures contracts

The value of energy trades can change over time as market conditions and underlying price variables change. A firm's portfolio risk is measured by evaluating the risk exposure from changes in any of the variables that affect existing contracts or the firm's projections from demand, supply and prices (Kaushik and Pirrong, 1999). A price forecast is the foundation for determining a firm's risk in managing their energy supply and their forward contracts for energy trades. Accurate price forecasting can therefore help reduce portfolio risk (Kaushik and Pirrong, 1999).

Analysis of expected return on assets based on "Value at-Risk" measures allows the firm to optimize the use of both physical and financial assets. Analysts can then determine the best use of physical and financial capital in order to maximize earnings (Wengler, 2001). As Parsons (1998) suggests, comprehensive risk management strategy that addresses both portfolio and operational risk, allows firms to

- avoid big losses due to price fluctuations or changing energy consumption patterns,
- reduce volatility in earnings while maximizing return on investment, and
- meet regulatory requirements that limit exposure to risk.

2.1. Price volatility and managing energy risk

Price volatility is at the heart of risk; yet it is an elusive concept that is hard to master and model. Volatility is usually defined as a measure for the magnitude of percentage changes in prices over time (Lintner, 1965).

According to the EIA report (2002) calls for competition in the power and gas industry, from the wholesale level to the retail level, have made deregulation an attractive option around the world. New market structures have been studied to search for a good one that can ultimately satisfy regulatory bodies, customers and suppliers.

The rise of competition and deregulation in power and gas markets has had a significant effect on prices so that the new market is relatively free and characterized by high price shifts. An unpredictable, volatile and risky environment has arisen and protection against market risk has become an essential issue.

In resource-based economies, such as those dependent on oil, exports and government revenues are uncertain and highly volatile. Uncertainty means that a variable, say, the oil price for the coming years, is simply unpredictable. In these economies oil price fluctuations not only affect the government budget considerably but also have strong effects on macroeconomic variables and even the stock market (Sadorsky, 1999). Given the effects of oil price volatility and the uncertainty, which is accompanied by these price movements, there is a great need for oil price risk quantification in these countries.

3. Value-at-Risk (VaR)

3.1. Definition

The term VaR did not enter the financial lexicon until the early 1990s, but the origins of VaR measures go further back. These can be traced to capital requirement for US security firms of the early 20th century. Starting with an informal capital test, the New York Stock Exchange (NYSE) first applied to member firms around 1922 (Hilton, 2003).

As Hendricks (1996) implies VaR is the maximum amount of money that may be lost on a portfolio over a given period of time, with a given level of confidence (Fig. 1). VaR describes the loss that can occur over a given period at a given confidence level, due to exposure to market risk (Hilton, 2003). The wide usage of the

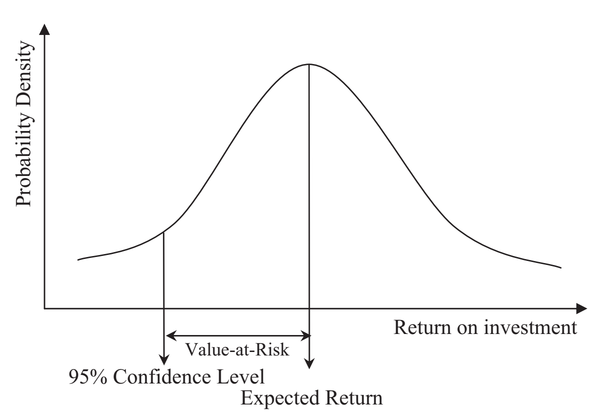

Fig. 1. VaR quantification using the probability density function of returns.

VaR-based Risk Management (VaR-RM) by financial as well as nonfinancial firms stems from the fact that VaR is an easily interpretable summary measure of risk and also has an appealing rationale as it allows its users to focus attention on "normal market conditions" in their routine operations (Basek and Shapiro, 2001).

Cabedo and Moya (2003) suggest that within oil markets, Value-at-Risk can be used to quantify the maximum oil price changes associated with a likelihood level. This quantification is fundamental when designing risk management strategies.

3.2. VaR quantification methods

There are several methods for calculating VaR. among them some methods are based on historical information that can be classified into three groups:

- Historical simulation Approach.
- Monte Carlo Simulation Method.
- Variance–Covariance methods (Hull and White, 1998).

In the Historical Simulation approach, an empirical distribution must be derived for the price changes over a period prior to the time of calculation. In the same way, for the Monte Carlo simulation method, an empirical distribution must be derived for the price changes. In this method some series of pseudo-random variables must be generated assuming that they follow a determined statistical distribution. Finally, within the Variance–Covariance methods it is assumed that potential loss is proportional to return standard deviation. Within the Variance–Covariance method VaR is estimated through:

$$\mathrm{VaR}_t = \lambda \sqrt{\theta}\, \mathrm{SDV}_{tp}, \tag{1}$$

where λ is the likelihood parameter, SDV_{tp} is the return standard deviation for time t; and θ is a parameter used when we calculate VaR for a time period with a length different from that used to estimate the standard deviation. Within the Variance–Covariance methods several methodologies can be used to calculate the VaR; among them Autoregressive Conditional Heteroskedasticity (ARCH) models are now very popular.

The original ARCH models were introduced by Engle (1982) and generalized by Bollerslev (1986) only few years later. Bollerslev's model characterizes the error term (ε_t) distribution in a general regression model conditional on the realized values of the set of exogenous variables (ϕ_{t-1}) as follows:

$$\varepsilon_t | \phi_{t-1} \sim N(o, h_t), \tag{3}$$

where normal distribution variance (h_t) can be expressed through

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \cdots + \beta_p h_{t-p}. \tag{4}$$

This model is known as a generalized ARCH model or GARCH (p,q) model, where p denotes the number of considered lagged variance values and q determines this number for the squared deviations.

4. The historical simulation approach

The Historical Simulation approach for VaR quantification contains two methods. One is the Historical Simulation Standard approach and the other the Historical Simulation ARMA Forecasting approach. What makes HSAF methodology different from the historical simulation standard approach is that the first does not directly use the distribution of past returns but rather the distribution of forecasting errors, derived from an estimated ARMA model.(Cabedo and Moya, 2001)

HSAF methodology, introduced and developed in this paper, requires a four-stage procedure (Fig. 2).

In the first stage the past returns are calculated and their stationary behavior analyzed. There are various methods for testing the stationary of series. Dicky Fuller and Augmented Dicky Fuller tests are now the most relevant tests for this end. If the results confirm the stationary behavior of the series, then the procedure should be continued by testing the autocorrelation behavior of the original series. If the stationary hypothesis is rejected, then the consecutive differences over the original series are required.

Whether the original series is stationary or not, the next stage is to test the autocorrelation behavior of the series. The Ljung–Box test calculation is then advisable at this point. If autocorrelation is not statistically significant, then the HSAF methodology is equivalent to the historical simulation standard approach. On the other hand, only when the analysis of the series determines a statistically significant autocorrelation level can the second stage of the procedure be implemented.

In the second stage, by applying Box–Jenkin's methodology and using past returns, a model for past returns behavior can be estimated. Ljung–Box autocorrelation tests are used again in this stage in order to determine the necessary number of lags to consider in order to remove the autocorrelation.

During the third stage, using the coefficients estimated in the second stage, forecasts are made for price returns. Using these forecasts the forecasting errors can be obtained. The statistical distribution of these errors is analyzed and the percentile associated with the desired likelihood level is calculated.

The final stage involves forecasting future returns using the model estimated in the second stage of the procedure. These forecasts are corrected by the percentile obtained in the previous stage. These corrected

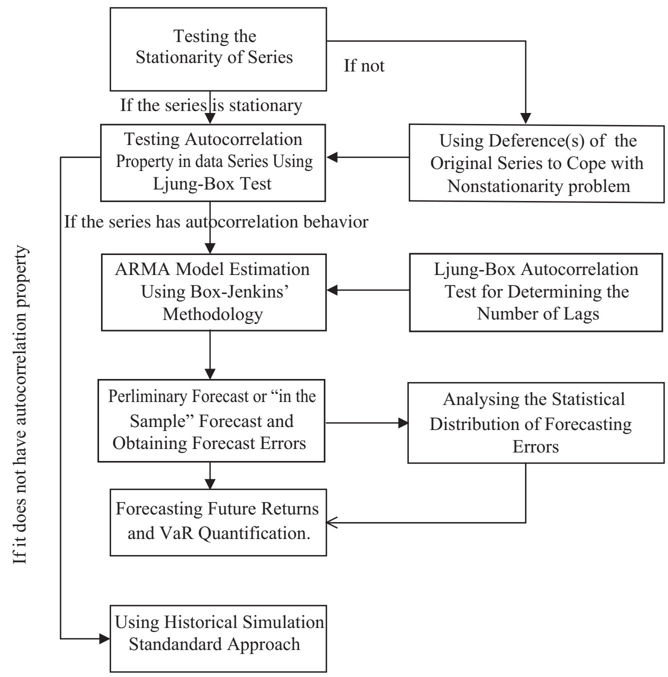

Fig. 2. The procedure for HSAF methodology implementation.

forecasts provide the value-at-Risk associated with a statistical likelihood level equivalent to the percentile used in the third stage.

5. Empirical results

5.1. Data

We used weekly OPEC prices from January 1997 to December 2003 and divided them into two periods: one from 1997 to 2002 which was used to estimate the model coefficients, and the other the year 2003, which was used for forecasting purposes (Fig. 3).

5.2. Historical simulation ARMA forecasting (HSAF) approach

As illustrated in Fig. 1, to apply the HSAF methodology we should follow a five-stage procedure. In the first stage we test the stationary of oil price series by applying ADF tests. Table 1 shows the result obtained. As results show the series is not stationary at conventional significant levels. To cope with this problem we used the first difference of series. Again we applied ADF tests. Table 2 shows the test results. As can be seen in this table, the first difference of the series is stationary at 99% level of confidence.

In the second stage we analyzed the autocorrelation functions of price returns by applying the Ljung–Box test. As can be seen in Table 3, the series show a statistically significant autocorrelation.

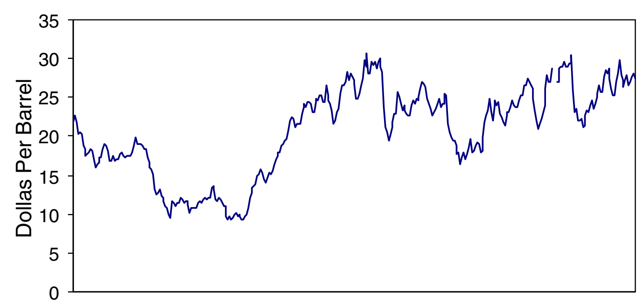

Fig. 3. Opec weekly oil prices January 1997–December 2003.

Table 1
ADF test statistics and critical values for the original series

1% Critical value	5% Critical value	10% Critical value
−3.4536	−2.8712	−2.5719
ADF test statistic:	−1.353785	

Table 2
ADF test statistics for the first- differenced series

1% Critical value	5% Critical value	10% Critical value
−3.4537	−2.8712	−2.5719
ADF Test Statistic:	−7.577756	

Stage 3 is devoted to the ARMA Model estimation. The method we used to estimate an ARMA model is Box–Jenkins. In this stage we estimated an AR(1) model. This estimation is according to the results obtained from analyzing Autocorrelation and Partial Autocorrelation functions. The estimation results are summarized in Exhibit 1.

Exhibit 1 Estimation results for AR(1) model

Variable	Coefficient	Std. error	*t*-Statistic
C	0.29553	0.140021	2.110612
AR(1)	0.222403	0.056164	3.959878

We also analyzed residuals ACF and PACF. The result indicated that there is no statistically significant autocorrelation in residuals (Table 4).

In stage 4, forecasts are made using the coefficients estimated in the third stage. We made these forecasts using the data provided by the "in the sample period" (1997–2002). Using these forecasts, we estimated the forecasting errors without any assumption about the skewness of the statistical distribution of the forecasting errors. We analyzed positive and negative forecasting errors separately and obtained the 99th percentile from their cumulative density function.

In the final stage, we used the model coefficients obtained in the third stage to forecast the future value of oil price changes. Actually this is an ex ante forecast.

Using the 99th percentile obtained in the previous stage, we corrected the future price changes. These corrected forecasts are the VaR estimations. The result of this VaR quantification together with actual price changes is shown in Fig. 4. As can be seen, the estimated VaR is greater than actual price changes for 97.6 percent of the forecast period. This is a similar percentage to the 99th likelihood level, which was expected before estimating VaR.

Table 3
Ljung–Box *Q*-statistics for the original series

Number of lags	*Q*-stat
12	35.442*
24	44.485*
36	48.181*

* Significant under 95% level of confidence

Table 4
Ljung–Box *Q*-statistics for the residuals of AR(1) models

Number of lags	*Q*-stat	Probability
12	15.154	0.233
24	25.232	0.393
36	32.776	0.623

5.3. The variance– covariance approach for VaR estimation

Among the various Variance–Covariance-based models for VaR quantification, Autoregressive Conditional Heteroskedasticity (ARCH) models are relatively the most advanced models. Using these models, we can forecast future variance values by combining past deviations and past values.

In applying HSAF methodology in Section 5.2 we analyzed the stationary and the autocorrelation behavior of the oil price series. We concluded there that although the original series is not stationary, its first difference is stationary. Also we found that price changes show an autocorrelation behavior, so we estimated an AR(1) model.

To estimate VaR through an ARCH scheme it is necessary to determine whether the price changes are suitable for this scheme. Fig. 5 illustrates oil price changes during 1992–2003. As can be seen in this graph, large oil price changes are followed by large changes and small changes are followed by small changes.

Although this suggests an ARCH scheme, we cannot rely only upon this criterion. So the suggested behavior was tested with the use of statistical tools. As

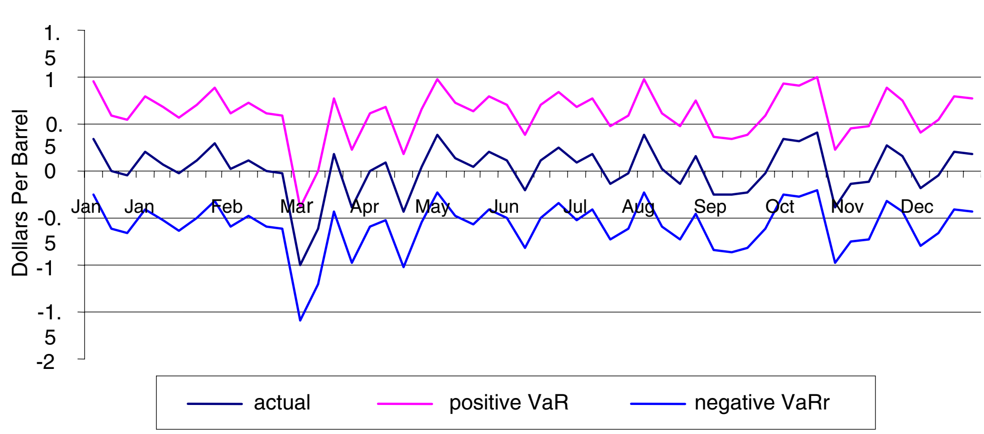

Fig. 4. Estimated VaR through HSAF methodology.

recommended by Enders (2004), using Ljung–Box statistic, we analyzed the autocorrelation behavior of the squared residuals of AR(1) model. Table 5 summarized the Q-Statistic values and their significant level. Results show that autocorrelation is statistically significant. So an ARCH scheme can be used to model the series behavior.

Several ARCH(p) and/or GARCH(p,q) models can be estimated for the analyzed behavior. To determine the best model, we used AIC and SBC model selection criteria. Table 6 reports the calculated values of AIC and SBC criteria for various models. Among them GARCH(1,1) presents the minimum values for both criteria. As Enders (2004) suggests, this model can be selected as the best model among others.

Using the estimated parameters of the GARCH (1,1) model, we forecasted variance values for the "out of sample" period. Also, the forecast obtained from the AR(1) model was used as the price changes of the year 2003.

Assuming that the values of standard deviation have a normal distribution, the corresponding value of the normal standard function for the assumed level of confidence was determined. Then we multiplied this value (2.33) by the forecasted standard deviations for the out of sample period. Finally, VaR was calculated by adding (for the positive returns) and subtracting (for the negative returns) the multiplication results to the return forecasts.

Fig. 6 shows the results of VaR estimation calculated through GARCH and HSAF methodologies. As shown the VaR calculated through HSAF methodology is more efficient. In other words, although the VaR estimated through Variance–Covariance methodology is more than actual price changes in 100% of the forecast period, due to its high variation from actual changes is less reliable than what is estimated through HSAF methodology.

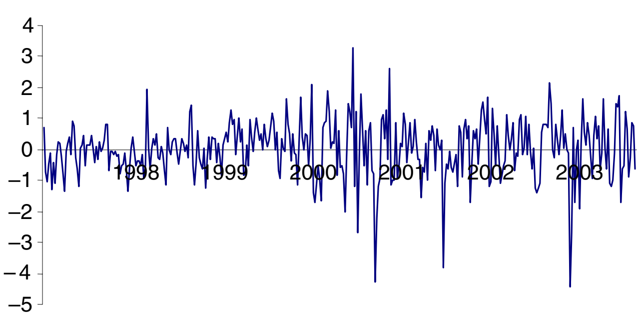

Fig. 5. OPEC weekly oil price changes 1997–2003.

Table 5
Ljung–Box Q-Statistics for the squared residuals of AR(1) model

Number of Lags	Q-stat
12	36.544*
24	60.472*
36	72.175*

* Significant at 95% level of confidence

Table 6
AIC and SBC model selection criteria for various ARCH/GARCH models

Model	AIC	SBC
GARCH(1,1)	2.498	2.546
ARCH(1)	2.584	2.621
ARCH(2)	2.58	2.628
ARCH(3)	2.581	2.64
ARCH(4)	2.579	2.65

6. Conclusions

Risk Management embodies the process and the tools used for evaluating, measuring and managing the various risks within a company's portfolio of financial, commodity and other assets. In energy markets, proper risk management depends not only upon proper portfolio analysis tools but also upon a solid foundation of forward price, volatility and option analysis.

Calls for competition in the power and gas industry, have made deregulation an attractive option around the world. The rise of competition and deregulation in turn has led to relatively free energy markets that are characterized by high price shifts. Within oil markets the volatile oil price environment after OPEC agreements in the seventies requires risk quantification.

Within oil markets, Value-at-Risk can be used to quantify the maximum oil price changes associated with a likelihood level. This quantification constitutes a fundamental point when designing risk management strategies. For this end, the paper proposes to quantify OPEC oil price VaR through various methodologies and to compare the result of VaR calculation through each. We used OPEC weekly oil prices from January 1997 to December 2003 for VaR calculation.OPEC oil price Value-at-Risk is calculated in this paper through Historical Simulation based on ARMA Forecasting (HSAF) and also Variance-Covariance based on GARCH modeling approaches. Results show that if the level of confidence is 99 percent, then the VaR calculated through HSAF methodology is greater than actual price changes in almost 97.6 percent of the forecasting period.We also concluded that although the estimated VaR through Variance–Covariance approach is greater than actual price changes in the whole forecasting period, it is not as efficient as what is calculated through HSAF methodology. Finally the

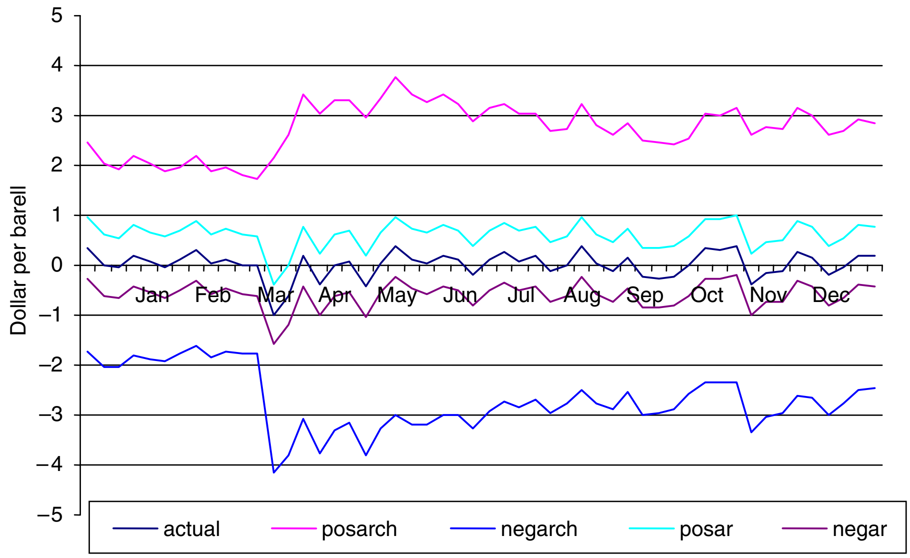

Fig. 6. OPEC oil price value at risk estimation through HSAF and GARCH methodologies.

conclusion is that Value-at-Risk, calculated by any method, is a reliable measure of oil price risk for whoever is concerned with oil price volatility, whether he (she) is a firm manager or a policy maker in the government body.

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