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Energy portfolio risk management using time-varying extreme value copula methods

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ABSTRACT

This work is concerned with the statistical modeling of the dependence structure between three energy commodity markets (WTI crude oil, natural gas and heating oil) using the concept of copulas and proposes a method for estimating the Value at risk (VaR) of energy portfolio based on the combination of time series models with models of the extreme value theory before fitting a copula. Each return series is modeled by AR-(FI) GARCH univariate model. Then, we fit the GPD distribution to the tails of the residuals to model marginal residuals distributions. The extreme value copula to the iid residuals is fitted and we simulate from it to construct N portfolios and estimate VaR. As a first step, the method is applied to a two-dimensional energy portfolio. In second step, we extend method in trivariate context to measure VaR of three-dimensional energy portfolio. Dependences between residuals are modeled using a trivariate nested Gumbel copulas. Methods proposed are compared with various univariate and multivariate conventional VaR methods. The reported results demonstrate that GARCH-t, conditional EVT and FIGARCH extreme value copula methods produce acceptable estimates of risk both for standard and more extreme VaR quantiles. Generally, copula methods are less accurate compared with their predictive performances in the case of portfolio composed of exchange market indices.

1. Introduction

Energy is an important input into the economics of the world. Large modification in energy commodity price can influence regional and global economic and financial performance. The price of energy commodities, like the price of all commodities, is subject to major swings over time, particularly tied to the overall business cycle. When demand for a commodity like oil exceeds production capacity, the price will rise quite sharply as both demand and supply are fairly inelastic in the short run. Since the early 2000s, prices for the majority of energy commodities have more than tripled and have set record highs. Energy market has become increasingly volatile and risky. For this reason, forecasting the future price of energy commodities and managing the risks associated with future energy prices have become an extremely crucial issue for central governments, businesses and corporations. One of the most popular tools to risk quantification is the well known "Value at Risk". The Value at Risk is defined as an amount of loss on a portfolio with a given probability over a fixed number of days. Value at Risk is considered as a benchmark for measuring market risk as it permit to reduce the risk associated with any kind of asset to just a single number that can be well understood by all interested parties. While the concept of VaR is intuitive, its modeling is a very challenging statistical problem.

Most empirical studies concerned with VaR estimation focused on market risk in stock and foreign markets (Bekiros et al., 2005; Byström, 2004, 2005; Di Clemente and Romano, 2003; Ghorbel and Trabelsi, 2008; Byström, 2004; Hotta et al., 2008; Huang and Lin, 2004; Mendes and Souza, 2004; Palaro and Hotta, 2006; Seymour and Polakow, 2003; Rockinger and Jondeau, 2006). In contrast, relatively little works have been done to quantify risk for energy commodities (Cabedo and Moya, 2003; Costello et al., 2008; Giot and Laurent, 2003; Hung et al., 2008; Sadeghi and Shavvalpour, 2006; Sadorsky, 2006). Giot and Laurent (2003) studied the performance of risk metrics, skewed Student APARCH and skewed student ARCH models to measure VaR of returns in aluminum, copper, nickel, Brent crude oil and WTI crude oil spot markets and in cocoa nearby futures markets. The skewed student APARCH model provides the best performances in all cases. Cabedo and Moya (2003) made comparisons between the performances of the historical simulation, historical simulation with ARMA process and variance–covariance method. They found that the second method delivers VaR forecasts that are superior to those obtained from GARCH.

Sadorsky (2006) used the daily closing futures price returns on WTI crude oil, heating oil, unleaded gasoline, and natural gas to study and compare the forecasting performance of a large number of models, which include both univariate and multivariate models using a wider array of forecast statistics than used in most other works. According to risk management view point, non parametric models outperform the parametric models in terms of number of exceedances in backtests as they provide the best VaR estimations.

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Costello et al. (2008) compared the ARMA with historical simulation to the semi-parametric GARCH model proposed by Barone-Adesi et al. (1999) and suggested that the semi parametric GARCH model generates VaR forecasts that are superior to the VaR forecasts from the ARMA with historical simulation as it is capable to capture volatility clustering. Huang et al. (2009) used daily spot prices of five energy commodities to compare the accuracy and efficiency of the VaR models. Empirical results show that GARCH model with heavy-tailed (HT) distribution is more accurate and efficient than alternatives for most cases at both low and high confidence levels and that fat tails in return innovation process indeed play an important role in the quantification of risk.

Fan et al. (2008) used GARCH model based on the Generalized Error distribution (GED), for both the extreme downside and upside, to measure VaR of returns in the WTI and Brent crude oil spot markets and proposed a Kernel-based test to detect risk spillover effect. They found that the GARCH-GED model appears more prudent and effective than that based on the standard normal distribution and historical simulation ARMA forecast (HSAF) method. Whether for upside or downside risk, both WTI and Brent returns have significant two way Granger causality in risk. In more recent works, Chiu et al. (2010) extend some individual and conventional VaR methods in literature (The EWMA, stable density, Kernel density, Hull and White, GARCH-GPD) by proposing their composite forecast for applying Brent and WTI crude oil prices. Such concept of compositing forecasts has not caught much attention in literature. Empirical results show that Hull and White method provides the most performance for capturing downside risk in the energy market. Moreover, the same work provided that combining VaR forecasts also provide acceptable and reasonable results. Fan and Jiao (2006) used an improved historical simulation approach to quantify VaR of crude oil price.

Huang et al. (2009) employ a new VaR approach extension of the CAViaR model to quantify oil price risk. The model proposed accommodates stochastic processes and satisfies the property of dynamic quantile. Aloui and Mabrouk (2010) computed the VaR for some major crude oil and gas commodities for both short and long trading positions using three GARCH models including FIGARCH, FIAPARCH and HYGARCH. They showed that considering for long-range memory, fat-tails and symmetry performs better in predicting a one-day-ahead VaR for both short and long trading positions. He et al. (2011) proposed to use the Morphological Component Analysis (MCA) based hybrid methodology for analyzing and forecasting the risk evolution in the crude oil market.

Few other works used EVT approach to quantify risk in energy markets. Krehbiel and Adkins (2005) analyzed the price risk in the NYMEX energy complex. Marimoutou et al. (2009) attempted a comparative study of the predictive ability of VaR estimates from various estimation techniques. The main emphasis has been given to the extreme value methodology and to evaluate how well EVT methods (unconditional and conditional) perform in modeling the tails of distributions and in estimating and forecasting VaR. Empirical results demonstrated the superiority of both conditional EVT and Filtered Historical Simulation (FHS) procedures and argued the importance of filtering process for the success of standard approaches.

To the best of our knowledge, risk market for energy commodities is rarely treated in multivariate context. In this sense, this work can perfectly contribute to this area of the literature. Multivariate GARCH models could not provide more accurate VaR estimates than univariate models because residuals of these models were assumed to follow multivariate normal distribution. Such hypothesis is too restrictive as energy markets are knowing these past few years turbulent periods and the occurrence of extreme events. For this reason, the aims of this paper are to follow the four-step approach as presented by Ghorbel and Trabelsi (2009) to compute VaR of 2 and 3-dimensional energy portfolio. This approach which combine GARCH models, EVT and copula functions has provided high quality of portfolio VaR forecast in the case of financial markets. We ask if it can provide the same performance in the case of energy portfolio. Our aim is to investigate the predictive performance of copula methods for n-dimensional energy portfolio VaR prediction and to compare them with a range of different methods (some versions of GARCH, MGARCH and EVT) and see if it works the best.

The outline of this paper is as follows. The next section explains the different conventional univariate and multivariate risk models employed in this study. Section 3 provides a brief review of unconditional and conditional extreme value theory (EVT). Section 4 offers a brief presentation of the copula methodology and it describes steps followed to estimate VaR using a (FI) GARCH extreme value copulas approach. Section 5 describes the data, presents an empirical analysis of different methods and examines the predictive performances of copula methods in estimating VaR of two- and three-dimensional energy portfolio. Section 6 delivers final remarks and conclusions. The Appendix offers technical and formal details to interested readers.

2. Conventional VaR methods

Value-at-Risk (VaR) is the most popular and usual risk measurement tool. In this paper, VaR represents the quantile of the energy portfolio return distribution. The right quantile is used to measure the upside risk which means the extra expenses for energy commodity purchasers caused by the sharp rise of energy portfolio value; whereas the left quantile is adopted to measure the downside risk that corresponds to the loss of sales income for energy producers caused by the decrease of energy portfolio return.

Formally, let $r_t = \log(p_t/p_{t-1})$ be the returns at time t where p_t is the price of an asset (or portfolio) at time t. We denote the $(1-p)$ % quantile estimate at time t for a one-period-ahead return as $VaR^p_{t+1/t}$, so that:

$$\Pr\left(r_{t+1} < \mathrm{VaR}^p_{t+1/t}\right) = p. \tag{1}$$

More formally, VaR is calculated based on the following equation:

$$\mathrm{VaR}^p_{t+1/t} = \hat{\mu}_{t+1/t} + F^{-1}(p)\hat{\sigma}_{t+1/t} \tag{2}$$

given that $F^{-1}(p)$ is the corresponding quantile of the assumed distribution, $\hat{\mu}_{t+1/t}$ is forecast of the conditional mean and $\hat{\sigma}_{t+1/t}$ is the forecast of the conditional standard deviation for $t+1$ given information at time t. The portfolio VaR is given by:

$$\mathrm{VaR}^p_{t+1/t} = \mu_{t+1/t,portf} + F_p^{-1}(p)\sigma_{t+1/t,portf} \tag{4}$$

where $F_p^{-1}(p)$ is the pth quantile of the assumed distribution of standardized portfolio returns, $\mu_{t+1/t,portf}$ is the forecast of the conditional mean portfolio and $\sigma_{t+1/t,portf}$ is the forecast of the conditional standard deviation portfolio.

2.1. Filtered historical simulation (FHS)

The historical simulation method assumes that historical distribution of returns will remain the same over time i.e. price change behavior repeats itself over time. For more volatile and turbulent periods, this method could provide a very bad measure of risk as it is based on the assumption that the series under consideration is independent and identically distributed which is not the case in the majority of markets. Moreover, measuring VaR with this method is extremely sensitive to the choice of the sample length n.

In order to remedy some of the shortcomings of HS method, various studies used the filtered historical simulation method which combines volatility models with the historical simulation in order to lessen the problematic use of the last method. FHS consists of fitting a GARCH model to return series and Historical simulation to infer the distribution of the residuals. By using the quantiles of the standardized residuals and