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Selection of Value at Risk Models for Energy Commodities

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In this paper we investigate different VaR forecasts for daily energy commodities returns using GARCH, EGARCH, GJR-GARCH, Generalized Autoregressive Score (GAS) and the Conditional Autoregressive Value at Risk (CAViaR) models. We further develop a Dynamic Quantile Regression (DQR) one where the parameters evolve over time following a first order stochastic process. The models considered are selected employing the Model Confidence Set procedure of Hansen et al. (2011) which provides a superior set of models by testing the null hypothesis of Equal Predictive Ability. Successively information coming from each model is pooled together using a weighted average approach. The empirical analysis is conducted on seven energy commodities. The results show that the quantile approach i.e. the CAViaR and the DQR outperform all the others for all the series considered and that, generally, VaR aggregation yields better results.

1. Introduction

The recent fluctuations of energy commodity prices have become a big concern for producers, consumers, governments and financial institutions. Short term price swings originating from picks and drops in demand or supply lead to time frames of high volatility and clustering. Such supply and demand imbalances can stem from the business cycle, political events or the behaviour of some market participants who engage in short term speculation, as discussed by Giot and Laurent (2003). In the long run, the evolution of prices sheds light on the health state of the world economy, revealing possible bubbles and stagnation periods. Numerous studies have focused on the effect of energy commodity fluctuations on the main economic indicators, their role in transmitting inflation and in inducing macroeconomic and financial adjustments (see for example Labys and Maizels, 1993). In his influential work, Hamilton (1983), for example, highlights that oil price shocks are partially responsible of U.S. recessions in the post-World War II period while Sadorsky (1999, 2003) found that oil price volatility shocks have asymmetric effects on the economy and provided evidence of the importance of oil price movements when explaining oscillations in stock returns. Cuñado and Pérez de Gracia (2003) reveal a cause-effect relationship between oil price changes and both inflation and economic activity. Moreover, Youssef et al. (2015) show that volatile oil prices may trigger the price variability of other energy commodities and can have widespread spillover effects on the international economy. Severe oil price oscillations also threaten the global industry, impacting on different players depending on where they lie on the value chain. For instance a fall in oil prices can decrease sales revenue for producers, reduce or eliminate the viability of production and decrease input costs for businesses consuming such commodities. Furthermore, as energy is a major component in inflation rate indices, the matter is relevant also to policy makers who adjust their targets on the basis of future trends in prices. Besides being used in industrial applications, energy commodities are extensively traded in the markets for trading and hedging strategies. Trading and financial firms widely use futures and option contracts to offset their positions against bear markets. Owing to the relatively competitive nature of deregulated oil markets, oil prices have become increasingly volatile and marked by high price shifts, see for example Hung et al. (2008). Due to this high volatility and risky environment, protection against market risk has become a necessity both for practitioners, corporations and public institutions, as discussed by Krehbiel and Adkins (2005). For this reason it becomes of crucial importance to model oil

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price movements and implement effective tools for energy price risk management.

Over the past decades a rich literature has flourished to propose valuable instruments for measuring and quantifying market risk. The most employed risk measure is the "Value at Risk" (VaR), defined as the worst expected loss of an asset or a portfolio given a certain confidence level and over a specific time period. In particular within energy markets, the VaR measure can be used to quantify the maximum oil price change associated with a given user defined confidence level. This quantification is fundamental for traders and financial institutions when designing portfolio risk management strategies aiming at avoiding unexpected large losses. Indeed, the trading strategy will achieve the intended results only when supported by an accurate assessment of risk. It is in this context that risk measurement becomes a crucial component of risk management in determining the appropriate modelling framework necessary to quantify commodity price risk exposure. Hence, VaR forecasts help risk managers to evaluate their exposure to significant unexpected losses and, consequently, to mitigate the overall riskiness of financial markets. In recent years, this issue has been addressed with a growing awareness by academics and practitioners, see among others: Pilipovic (1998), Hung et al. (2008), Alizadeh et al. (2008), Giot and Laurent (2003), Marimoutou et al. (2009), Fan et al. (2008), and Aloui and Mabrouk (2010).

Studies on energy commodities' prices and VaR forecasting considered in literature, show that the returns exhibit most of the well known stylized facts like fat tails, leptokurtosis, leverage effect and volatility clustering. Recently several models have been considered in order to replicate them. In their work Hung et al. (2008) analyse the daily spot prices of West Texas Intermediate (WTI) crude oil, Brent crude oil, Heating oil #2, Propane and New York Harbor Conventional Gasoline Regular suggesting that GARCH models with the Heavy-Tailed (HT) distribution proposed by Politis (2004) yields better results against the GARCH with the Normal and the Student-t distribution. The HT-GARCH model produces more satisfactory results in terms of accuracy and efficiency, whereas the Normal-GARCH and Student-t-GARCH ones tend to overestimate and underestimate the tail risk, respectively. Therefore, the choice of a suitable distribution of the return innovation term plays a key role in VaR estimation. Moreover, Youssef et al. (2015) adopt long memory processes including, FIGARCH, HYGARCH and FIAPARCH to better capture heteroscedasticity, asymmetry and fat tails in the crude oil and gasoline market. Their findings show that taking into account for long-range memory, asymmetry and fat-tailed distributions helps predicting VaR in the highly volatile energy market. In their work, Xiliang and Xi (2009) evaluate and compare GARCH models with Gaussian and Generalized Error (GED) distributions with the CAViaR ones, proposed by Engle and Manganelli (2004), for daily spot prices of WTI crude oil and Brent crude oil. They suggest that both models perform well for the low confidence level, i.e. 95%. However, in accordance with the previous literature, at the higher 99% confidence level the Normal-GARCH performs poorly, whereas the GARCH with heavy-tailed distributions and all CAViaR specifications work better.

In this work, we compare, from a VaR forecasting point of view, several univariate econometric and statistical models some of which are already used in the energy commodity literature while others are relatively new in this context. The intent is to find the model that predicts VaR accurately and replicates the stylized facts encountered in energy commodity time series. We rely on two of the models already well established in the energy commodities' literature, i.e. GARCH with different error term distributions and the four CAViaR specifications proposed by Engle and Manganelli (2004). Moreover in order to account for the asymmetric impact of negative shocks on the volatility, we include the Exponential GARCH (EGARCH) of Nelson (1991) and the GJR-GARCH model of Glosten et al. (1993). In addition, we propose to consider the Generalized Autoregressive Score (GAS) models which have never been used in modelling commodity prices and we develop a new Dynamic Quantile Regression (DQR) model which is able to capture the dynamic time varying characteristics of the energy commodities' time series. The GAS models, recently introduced by Creal et al. (2013) have emerged as a worthy alternative to GARCH ones in terms of volatility and VaR modelling. The key factor of those models is the updating mechanism of the parameters over time via the scaled score log-likelihood. In particular the GAS encompass the GARCH models having the advantage of exploiting the complete density of the returns, rather than the first and second order moments. This specification allows to better represent the time varying volatility of the asset prices and to understand the commodity past and future price behaviour. Such models have been applied for VaR estimation of stock market indices returns by Ardia et al. (2016) and Bernardi and Catania (2016) and for individual stocks and exchange rates by Lucas and Zhang (2016) but never, to the best of our knowledge, to energy commodities. Considering that the primary goal is VaR estimation, the new model hereby proposed is the Dynamic Quantile Regression (DQR) one, which models directly the quantiles of the returns without imposing any parametric assumption on the error term. For this model, the time varying regression parameters evolve over time following a first order stochastic process able to catch the dynamic nature of the time series. The DQR, as we will show, is able to capture the well known stylized facts of the energy commodities and to forecast the VaR measure even for very high confidence levels, that is in those situations where a miscalculation of risk can be extremely costly and may involve potentially massive losses.

Building models able to predict VaRs efficiently is of utmost importance since they are useful only if they predict future risks accurately. For this reason, it is quite relevant to evaluate the quality of the VaR estimates by performing a set of targeted tests. Nowadays, in the context of risk management, backtesting is the most recognized test procedure; see, for instance, Roccioletti (2015), Jorion (2006), Alexander (2009), McNeil et al. (2015), and Christoffersen (2009). Thus we use this procedure to have a first insight on the accuracy of the estimated VaR provided by the different models considered throughout the paper. Moreover, in order to give a more in depth analysis, given that several models may be available after the backtesting process, we propose a method for selecting the best or a subset of best ones given a certain criteria. This is a matter of practical concern, in fact, usually the asset manager has to count on a restricted number of fruitful and reliable models rather than to deal with different ones. Some of the methodologies developed in the literature on this topic are the Reality Check of White (2000), the Stepwise Multiple Testing procedure of Romano and Wolf (2005) and the Conditional Predictive Ability test of Giacomini and White (2006). Beyond these, here we investigate the Model Confidence Set (MCS) approach proposed by Hansen and Lunde (2005) and Hansen et al. (2011). This procedure, given a certain confidence level, performs a sequence of statistical tests to construct a subset of superior models with equal predictive ability with respect to an arbitrary loss function. The resulting sample of models is known as "Superior Set of Models" (SSM). Ideally the SSM is of dimension one; nevertheless this won't be the case very often, either because of the poor information coming from the data or because the considered models are, instead statistically equivalent. The presence of several compelling models with the same predictive ability points out the issue of combining different VaR estimates. As argued by Giacomini and Komunjer (2005), the combination of VaR models is beneficial and it may strengthen individual forecasts, see Bernardi et al. (2017a). The choice of the combination weights, which is decisive to gauge the relative performance of this technique, is reviewed more thoroughly by Pesaran et al. (2009). Here we propose to gather the information coming from the models belonging to the SSM by using the test statistics calculated in the MCS procedure itself.