Energy Economics 38 (2013) 64–76

Contents lists available at SciVerse ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Energy risk management through self-exciting marked point process

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ARTICLE INFO

Article history:
Received 25 May 2012
Received in revised form 4 March 2013
Accepted 6 March 2013
Available online 18 March 2013

JEL classification:
C22
G15
G32
Q47

Keywords:
Extreme value theory
Energy market risk
Energy forecasting
Value at Risk
Marked self-exciting point process

ABSTRACT

Crude oil is a dynamically traded commodity that affects many economies. We propose a collection of marked self-exciting point processes with dependent arrival rates for extreme events in oil markets and related risk measures. The models treat the time among extreme events in oil markets as a stochastic process. The main advantage of this approach is its capability to capture the short, medium and long-term behavior of extremes without involving an arbitrary stochastic volatility model or a prefiltration of the data, as is common in extreme value theory applications. We make use of the proposed model in order to obtain an improved estimate for the Value at Risk in oil markets. Empirical findings suggest that the reliability and stability of Value at Risk estimates improve as a result of finer modeling approach. This is supported by an empirical application in the representative West Texas Intermediate (WTI) and Brent crude oil markets.

1. Introduction

In recent years oil industry has been continuously expanding and evolving with no sign of change in the near future. Price fluctuations in the crude oil markets worldwide have attracted significant attention from both, managers and academics, due to the profound impact created on businesses and governments, and due to the high complexity and wide price swings in times of shortage or oversupply. In addition, oil futures are becoming an important investment instrument. For example, oil futures became an important hedge during the Subprime mortgage crisis in 2007 to 2008. Oil is considered to be a hedge at such times as it goes against the trend of the stock market. Unfortunately, due to the complicated unusual nature of oil price fluctuations, current energy risk management practice has remarkable difficulty assessing the likelihood and magnitude of extreme events in these markets. Examples of extreme events are the changes in crude oil prices, which affect oil market traders, and impact global economic activity, government policy and vice versa. For instance, the Persian Gulf War in 1991 is recognized as one of the most serious events that strongly affected crude oil markets in the 1990s. By extreme events in oil markets, we mean events that occur infrequently and that seem to cluster on a non-regular basis, making the study of their behavior even more complicated. In particular, the stylized facts related to the oil price fluctuations, such as the irregular spacing in time, the cluster of extremes as well as the presence of strong discreteness of price change correlation within the time duration among extreme events, make new econometric approaches that take these issues into consideration necessary. This methodological limitation is unfortunate because infrequent, but potentially significant, events are precisely the kind of events that need the most attention and, with appropriate attention, they can also produce the greatest benefits.

One of the most popular and attractive methods of measuring risk is the Value at Risk (VaR), which provides a single number that summarizes the total risk for financial assets. VaR literature in crude oil markets is mainly based on standard Historical simulation, Variance and Covariance methods, and GARCH modeling. For instance, Sadeghi and Shavvalpour (2006) use weekly OPEC prices from January 1997 to December 2003 for VaR calculation. According to their results Historical simulation ARMA forecasting (HSAF) is more efficient for the period in question. Fan et al. (2008) analyze the extreme downside and upside VaR of daily returns in the WTI and Brent crude oil spot markets between 1987 and 2006. The results of the empirical study indicate that the Generalized Error Distribution-GARCH-based VaR approach seems more effective than the HSAF. From the point of view of Extreme Value Theory (EVT), most of the studies focus on the conditional extreme value method introduced by McNeil and Frey (2000) in order to estimate VaR and related risk statistics from the tails of conditional distributions for these commodities. For instance, Krehbiel and Adkins (2005) estimate tail parameters and construct risk statistics for unconditional distributions of daily logarithmic price changes of the

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http://dx.doi.org/10.1016/j.eneco.2013.03.003

NYMEX energy complex. Their empirical results indicate that, for the backtesting, the conditional extreme value approach is significantly more accurate for measuring the risk exposure of most of the series examined. Marimoutou et al. (2009) utilize standard EVT to model VaR for long and short trading positions in the oil market by applying both unconditional and conditional EVT models to forecast VaR. They compare these models to the performances of other well-known modeling techniques, such as GARCH, Historical simulation and Filtered Historical Simulation. The results of this work show that both conditional EVT and Filtered Historical Simulation procedures offer the greatest improvement over other methods. Finally, Ren and Giles (2010) analyze daily returns of crude oil prices in the Canadian spot market between 1998 and 2006 through an unconditional approach. Their empirical results show that the risk measures obtained through this approach provide quantitative indicators for investment decisions in the Canadian crude oil market. In this paper we will consider two alternative generalizations for the classical point process theory in EVT, by means of marked self-exciting point process (MSEPP) theory. A point process is defined as MSEPP, when the past evolution can impact the probability of future events and it is only based on the extreme observations, contrary to the above approaches where we need to model the whole data set. The contribution of this paper is two-fold. First, it explores dynamic EVT models that can capture the short-term dynamic of extreme events in crude oil markets without the use of an arbitrary stochastic volatility model, which impacts the measures of risk, such as VaR.

The method to be introduced takes advantage of the structure of the model, thus allowing for more efficient use of the data. The first class of models is formulated in relation to the time of occurrence of the extreme events (Chavez-Demoulin and McGill, 2012; Chavez-Demoulin et al., 2005; Herrera and Schipp, 2009). We call this class of models time event peaks over threshold (TE-POT) and it would be able to generate power-law (ETAS model) and exponential decay (Hawkes model) between extreme events and short term cluster burst. The second class of models is the autoregressive conditional duration peaks over threshold (ACD–POT). It is focused on the intervals between extreme events, the inter-exceedance times (Herrera and Schipp, submitted for publication), and it is able to produce slow decay of autocorrelation and medium- and long-term cluster bursts.

The second contribution of this paper is the empirical application of the proposed models to two well known crude oil markets; the West Texas Intermediate (WTI), which trades on the New York Mercantile Exchange (NYMEX), and the Brent oil market, which is the leading global price benchmark for Atlantic basin crude oils and is used to price two thirds of the world's internationally traded crude oil supplies. Our results show that the MSEPP models are stable and reliable, not only in sample results but also in the backtesting, implying that these approaches of modeling extreme values can be used for further applications in energy markets. Moreover, major improvements in VaR forecasting are achieved in all aspects when accounting for the extreme event dynamics by means of the proposed models. In particular, VaR violation ratios are statistically equal to the theoretical values in all cases, and VaR violations are independent when using either the TE-POT model or the ACD–POT model, the latter being preferred overall.

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The remainder of the paper is organized as follows. Section 2 offers a brief review of the classical EVT approach. Section 3 introduces the new general MSEPP specification for extreme events. Furthermore, in this section we describe the two self-exciting approaches to be used in the empirical study. Section 4 contains the empirical applications. Section 5 concludes.

2. Peaks over threshold (POT) method

Suppose that we can observe the returns through the time of a crude oil market, as for example the Brent market. We denote these observations by $Y_1, \ldots, Y_n$ and we assume that the return series are independent and identically distributed (iid) random variables with common distribution function F.

Now, imagine that we observe this random distribution of observations $\{(t_i, y_i)\}$ whose values exceed a high threshold u in a defined state space $\mathscr{T} \times \mathscr{Y} = [0,1) \times [u,\infty)$, where the time has been rescaled for convenience to the interval (0,1). By looking at the dynamics of such observations, we concentrate only on the most extreme oil market returns.

On one hand, the time events t_i are the time of the i-th peak exceedance, i.e., the time in that a return exceeds a defined high threshold u. We refer to this process as the ground process. On the other hand, $y_i - u$ is the exceedance sizes or marks for a sufficiently high threshold u and we will call this process the process of the marks. A point process $N(A)$ can be viewed as the counter of these random observations in a set $A \subseteq \mathscr{T} \times \mathscr{Y}$. Pickands (1971) demonstrated that this two dimensional point process will look like as a non-homogeneous Poisson process with intensity defined for all subsets of the form $A = [t_1, t_2) \times [y,\infty)$ where t_1 and t_2 are times of occurrence of extreme events. This representation is as follows

$$\lambda(t,y) = \frac{1}{\sigma}\left(1+\xi\frac{y-\mu}{\sigma}\right)_+^{-1/\xi-1}, \tag{2.1}$$

where $y_+ = \max(y,0)$. In this point process μ and σ determine the location and scale of the extremes, while ξ characterizes the rate of decay of the tail of the distribution of extreme events. It follows from these characterizations that a complete summary of extremal behavior of this time series is contained in the three parameters μ, σ, and ξ.

If we accept that the point process of exceedances is a one-dimensional Poisson, then the process has independent increments, i.e., the number of events t_i that occur in disjoint time intervals is mutually independent, which implies lack of memory in the evolution of the process. In addition, the number of extreme events t_i in any interval of length $(t_2 - t_1)$ is Poisson distributed with mean

$$\Lambda([t_1,t_2) \times [y,\infty)) = \int_{t_1}^{t_2}\int_y^{\infty}\lambda(l,s)\,ds\,dl = \Lambda_1([t_1,t_2)) \times \Lambda_2([y,\infty)).$$

Notice that we have divided the intensity measure Λ into two independent Poisson processes with corresponding intensity measures Λ_1 and Λ_2. The first, Λ_1, models the random time at which the extreme events occur, while the second, Λ_2, models the exceedance sizes.

Another important result of extreme value theory is the following limiting conditional probability, which characterizes the tail of the excess distribution function over the threshold u.

$$\mathbb{P}(Y-u \le y | Y > u) = \frac{\Lambda_2([y+u,\infty))}{\Lambda_2([u,\infty))} = \left(1+\frac{\xi y}{\sigma+\xi(u-\mu)}\right)^{-1/\xi} = \overline{G}_{\xi,\beta}(y), \tag{2.2}$$

which is just the survival function of the generalized Pareto distribution (GPD), i.e., $\overline{G} = 1-G$, with scaling parameter $\beta = \sigma + \xi\,(u-\mu)$ for $0 \le y < y_F$. Here y_F is the right endpoint with values $y_F = \infty$ if $\xi > 0$ and $y_F = -\beta/\xi$ if $\xi < 0$. We shall call this model the peaks over thresholds or POT model.

Observe that this methodology does not take into account the time when these extreme events occur because this assumes that