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Spikes and crashes in the oil market

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ABSTRACT

Over the last three decades, advanced economies have been facing a substantial rise not only in the crude oil price, but also in the oil price volatility. Quantifying the tail risk has become a prominent issue for investors and policy makers given the repeated spikes and crashes during previous years. This article reveals the existence of a tail risk hidden in the oil market by applying, for the first time, an extreme value theory analysis with a quantile regression procedure. An empirical test is carried out on the daily West Texas Intermediate (WTI) crude oil prices from 1983 to 2013. The main results indicate that the WTI becomes extreme from a daily variation of +5.0% and −10.0%. In addition, the maximum one-day variation which should be exceeded only once per century is +23% and −33%. Finally, the tail risk is overall borne by the oil-importing countries. The main policy implication of these findings is to design policy measures that consider the existence of price-volatility thresholds above/below which the oil market becomes unstable.

1. Introduction

The rise of the US benchmark oil West Texas Intermediate (WTI) to 145 USD per barrel on July, 3 2008 and its collapse to under 30 USD per barrel on December, 23 2008 constitutes the largest daily nominal swing in the history of oil. These type of swings tend to generate more and more spikes and crashes. Lammerding et al. (2013) believe that it might be due to the heavily financialized market. Simultaneously, WTI volatility – as proxied by the OVX implied volatility index – climbed from 0.37 to 1.14. Hence, the oil market exhibits a tail risk characteristic that is higher than for the stock market. For instance, the Black Monday fostered the highest one-day volatility level equal to 1.25 in the US stock market on October 19, 1987. For comparison purposes, the Operation Desert Storm triggered the highest one-day volatility level of 2.0 in the US oil market on January 18, 1991. Besides, Sornette et al. (2009) notice that geopolitical events tend to participate in raising the level uncertainty. Generally speaking, crude oil markets are characterized by high levels of volatility due to economic, financial and politic uncertainties related to supply, demand, OPEC strategies, speculators and other factors affecting non-OPEC oil production (see Boussena and Locatelli, 2005). Indeed, the price fluctuations of petroleum products have become a great concern to economic agents such as consumers, producers and even speculators (e.g. hedge funds). Higher oil prices used to hurt advanced economies, whereas oil price volatility affects the oil industry revenues. More generally, Sadorsky (1999) finds that oil prices and oil price volatility both play important roles in affecting real stock returns. Hence, sudden variations in oil

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prices have contributed to create a climate of uncertainty for developed economies, industry and service sectors in different economies, as well as consumers. For instance, Bagliano and Morana (2014) find that fluctuations in the financial fragility index can be attributed to identified macroeconomic (20%) and financial disturbances (40–50%), to oil-supply shocks in the long-term (25%). Various events may lead to these unexpected oil price/volatility variations such as political instability in oil-exporting countries, political tensions in the MENA region, climatic effects or natural disasters (Fattouh and Scaramozzino, 2011). In addition, such market shocks imply either a reduction of oil supply or an increase oil demand. In any case, what matters is the surprise effect, corresponding to an increase in hidden risks of low probability events, popularized by Taleb (2010) under the concept of 'Black Swan'.

To our best knowledge, the tail risk behavior (characterized by spikes and crashes) of the crude oil market has not been examined using the extreme value theory (EVT) with a quantile regression analysis. This paper aims at filling this gap in the literature. A general discussion on the application of EVT to risk management is proposed by Embrechts et al. (1997), McNeil (1999), Beirlant et al. (2004). Previous studies such as Marimoutou et al. (2009), Ren and Giles (2010) or Zikovic (2011) address the issue of tail risk in the crude oil market. However, the results stemming from EVT applications are usually difficult to interpret due to the use of standardized returns. Indeed, the methodology involves several steps: (i) extract the standardized residuals by filtering the raw returns with a GARCH model, (ii) run some standard tests to check for the approximate independent and identically distributed nature of the standardized returns, and (iii) finally apply EVT. In the first step, the standardized returns have no economic meaning in the real world. In clear, without reconverting the standardized returns to raw returns through a quantile regression, it is not possible to interpret economically the statistical inference made by the EVT analysis. Quantile regression adds value by allowing the results from EVT to be transformed into real world values, i.e., raw returns.

To bypass this problem, this article applies, for the first time, a simple linear transformation of the standardized returns from EVT results into (theoretical) raw returns using quantile regressions. Quantile regression can be seen as an extension of OLS estimation with a better consideration brought to extreme observations.

This methodology is implemented on the WTI crude oil daily prices from 1983 to 2013. To presage our results, our analysis reveals the existence of a tail risk, with a possible magnitude of one-day crash higher than +23% or −33% once per century. Besides, some economic interpretations and policy implication are derived.

The remainder of the article is organized as follows. Section 2 opens with a brief review of the extreme value theory applications in finance. Section 3 details the data. Section 4 contains the empirical results. Section 5 summarizes the main findings and concludes.

2. EVT description

2.1. Tail distribution

A theorem from Balkema and de Haan (1974) and Pickands (1975) shows that when the threshold u is sufficiently high, the distribution function of the excess beyond this threshold can be approximated by the Generalized Pareto Distribution (GPD):

$$G_{\xi,\beta}(x) = \begin{cases} 1-(1+\xi x/\beta)^{-1/\xi}, & \text{for } \xi \neq 0 \\ 1-\exp(-x/\beta), & \text{for } \xi = 0 \end{cases} \tag{1}$$

where $\beta \geq 0$ and where $x \geq 0$ when $\xi \geq 0$, and where $0 \leq x \leq -\beta/\xi$ when $\xi < 0$. β is a scaling parameter. ξ is the tail index. The tail index is an indication of the tail heaviness: the larger the ξ, the heavier the tail. This distribution encompasses other types of distributions. More particularly, if $\xi > 0$, then it is a reformulated version of the ordinary Pareto distribution.

Let us consider x_m as the return level that is exceeded on average once every m observations. The return level measure (Gumbel, 1941) highlights the effect of extrapolation, which is useful for forecasting, even if scarcity produces large variance estimates. Let ζ_u be the probability of exceeding the threshold u. Return levels are expressed with an annual scale, so that the N-year return level is the level expected to be exceeded once every N years. n_{250} is the average number of trading days per year, with $m = N \times n_{250}$. It comes for the N-year return level:

$$x_m = u + \frac{\sigma}{\xi}\left[(N \times n_{250}\zeta_u)^{\xi} - 1\right] \tag{2}$$

2.2. Threshold selection

Extreme value statistical analysis has been initially dedicated to weather, climate or seismic analysis. Threshold selection is a central issue, whatever the field of study. For example, scientists, in hydrology, study the risk associated with flooded rivers where rising water represents a threat for inhabitants. In that case, they will determine the minimum threshold of overflow. The more appropriate statistical approach in that case is the extreme value theory toolkit, where this threshold is considered as the extreme risk modeled by a General Pareto distribution for instance.

Threshold selection is subject to a trade-off between: finding a high threshold where the tail estimate has a low bias with a high variance, or finding a low threshold where the tail estimate has a high bias with a low variance. There are two