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Jumps and stochastic volatility in crude oil futures prices using conditional moments of integrated volatility

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ABSTRACT

We evaluate alternative models of the volatility of commodity futures prices based on high-frequency intraday data from the crude oil futures markets for the October 2001–December 2012 period. These models are implemented with a simple GMM estimator that matches sample moments of the realized volatility to the corresponding population moments of the integrated volatility. Models incorporating both stochastic volatility and jumps in the returns series are compared on the basis of the overall fit of the data over the full sample period and subsamples. We also find that jumps in the returns series add to the accuracy of volatility forecasts.

1. Introduction

The volatility of commodity futures prices has become a topic of increasing interest in recent years for academic researchers, practitioners and those involved with the regulation of derivatives markets. Many commodity futures markets have become increasingly 'financialized' over the past decade as financial firms with no inherent exposure to the commodity have adopted a strategy of portfolio diversification into commodity futures as an asset class.

Although this trend has affected many commodity futures markets, it has had a marked impact on one of the most important markets: that for derivatives of crude oil, which is now the most heavily traded commodity futures contract by volume. Crude oil, as a key global commodity, has experienced considerable price level variation in the boom preceding the global financial crisis in 2008 and the ensuing Great Recession. A major oil price shock in 2008 was caused by constraints on the production of crude oil paired with low elasticity of demand (for details, see Hamilton (2009) and Kilian (2009)). This shock, while being caused by fundamentals, was clearly exacerbated by financial speculation and 'financialization' of commodities. Variation in oil price levels has been accompanied by wide variations in the volatility of returns. In the futures markets, returns exhibit heavy tails, autocorrelation, and volatility clustering, leading to significant challenges in modeling their first and second moments.

Both the International Monetary Fund (IMF) and the Federal Reserve Board (see Alquist et al., 2011; IMF, 2005 p. 67, 2007, p. 42) use futures prices as the best available proxy for the market expectations of the spot crude oil price.

Like many financial series, commodity futures prices are likely to exhibit random-walk behavior. Such behavior in crude oil futures prices implies that a model of prices or returns is not likely to beat the naïve model. However, even if returns are not forecastable, their volatility may be successfully modeled. In this paper, we employ various models of stochastic volatility in order to analyze the *uncertainty* of crude oil futures returns and to evaluate the forecastability of their volatility. The empirical analysis makes use of high-frequency (tick-by-tick) data from the futures markets, first aggregated to 10-minute intervals during the trading day. The intraday variation is then utilized to generate daily time series of prices, returns and realized volatility.

Our sample period of October 2001 to December 2012 is characterized by high frequency fluctuations and fat tails. This is an appropriate setting for our investigation of the role of jumps (modeled as *extreme events*). Before performing any model estimation, we employ non-parametric methods to identify the periods when these *extreme events* might have occurred. Our empirical findings are in line with these test results indicating a very high volatility during 2008.

The high frequency data allows us to test various models for oil futures returns using a straightforward Generalized Method of Moments

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(GMM) estimator that matches sample moments of the realized volatility to the corresponding population moments of the integrated volatility in the spirit of Bollerslev and Zhou (2002). These models are then compared, in terms of overall fit of the data and forecast accuracy statistics, over the full sample. The model with stochastic volatility and jumps is also tested over a sub-sample (January 2006–December 2012) to address structural stability (as in Andersen et al., 2002). Key findings include the importance of both jumps and stochastic volatility in oil futures returns and the apparent unimportance of leverage as a modeled component.

The wider applicability of this method of estimation to other markets is outside the scope of this paper, but an interesting topic for future research.

2. Review of the literature

Schwartz (1997), Schwartz and Smith (2000), Casassus and Collin-Dufresne (2005) propose multi-factor models for energy prices where returns are only affected by Gaussian shocks only, but constrain volatility to be constant. Pindyck (2004) examines the volatility of energy spot and futures prices, estimating the standard deviation of their first differences. Askari and Khrichene (2008) fit jump-diffusion models to futures on Brent crude oil. Trolle and Schwartz (2009) propose a multifactor stochastic volatility model for pricing futures and options on light sweet crude oil trading on the NYMEX. Using daily data, they present evidence that taking account of stochastic volatility improves pricing, but they consider the inclusion of jumps to be less important. Vo (2009) estimates a multivariate stochastic volatility model using daily data on the West Texas Intermediate (WTI) crude oil futures contracts traded on the NYMEX and finds that stochastic volatility plays an important role.

Larsson and Nossman (2011) find evidence for stochastic volatility and jumps in both returns and volatility daily spot prices of WTI crude oil from 1989 to 2009.

The role of volatility as a measure of uncertainty of oil price futures is stressed by Bernanke (1983) and Pindyck (1991) who show that this measure of uncertainty is extremely relevant for firms' investment decisions.

Our contribution lies in the use of the information on volatility of oil futures returns provided by high frequency, intra-day data while focusing on the role of volatility as measure of variability and uncertainty of oil price forecasts.

3. Data description

We exploit the distributional information embedded in high-frequency (10-minute interval) intraday futures price quotations on crude oil in order to test for the presence of stochastic volatility and jumps in crude oil futures returns.

Light, sweet crude oil (West Texas Intermediate) began futures trading on the New York Mercantile Exchange (NYMEX) in 1983 and is the most heavily traded commodity future. Crude oil futures trade in units of 1000 U.S. barrels (42,000 gallons), with contracts dated for 30 consecutive months plus long-dated futures initially listed 36, 48, 60, 72, and 84 months prior to delivery. Additionally, trading can be executed at an average differential to the previous day's settlement prices for periods of two to 30 consecutive months in a single transaction. Crude Oil Futures are quoted in dollars and cents per barrel.

The raw data used in this study are 10-minute aggregations of crude oil futures contract transactions-level data provided by TickData, Inc. For each 10-minute interval during the day trading session and for each traded contract, the open, high, low, close prices are recorded, along with the volume of trades in that interval. For the purpose of computing returns, the trading session's close price and the following trading session's close price are used to produce an estimated overnight (or over-the-weekend) return.

Industry analysts have noted that to avoid market disruptions, major participants in the crude oil futures market roll over their positions from the near contract to the next-near contract over several days before the near contract's expiration date. A continuous price series over contracts, which expire monthly, is created by hypothetically rolling over a position from the near contract to the next-near contract three days prior to expiration of the near contract.

The returns series and the realized volatility measures are displayed in Fig. 1 and their descriptive statistics are given in Table 1 (descriptive statistics for a shorter time series, January 2006 - December 2012, can be found in Table 2). Both series exhibit excess kurtosis, while the realized volatility series has a large skewness coefficient. The Kolmgorov–Smirnov test for normality rejects its null for both series, while the Shapiro–Francia test (1972) for normality concurs with those judgements. The Box–Pierce portmanteau (or Q) test for white noise rejects its null for both series. The daily returns series exhibits significant ARCH effects at 1, 5, 10 and 22 lags, while no evidence of ARCH effects is found in the realized volatility series.

4. Estimation method

Following Bollerslev and Zhou (2002), who use continuously observed futures prices on oil, we build a conditional moment estimator for stochastic volatility jump-diffusion models based on matching the sample moments of realized volatility with population moments of integrated volatility. In this context, as Andersen and Benzoni (2008) have suggested, realized volatility serves as a non-parametric ex post estimate of the variation in returns. In this paper, realized volatility is computed as the sum of high-frequency (10-minute interval) intraday squared returns.

4.1. No-jump case

The returns on futures at time t over the interval $[t-k, t]$ can be decomposed as

$$r(t,k) = \ln F_t - \ln F_{t-k} = \int_{t-k}^{t} \mu(\tau)d\tau + \int_{t-k}^{t} \sigma(\tau)dW_\tau.$$

The quadratic variation or integrated variance, which coincide in the no-jump case, can be expressed as

$$QV(t,k) = IV(t,k) = \int_{t-k}^{t} \sigma^2(\tau)d\tau.$$

In discrete time, the corresponding sample realized variance (RV) can be described as

$$RV(t,k,n) = \sum_{j=1}^{n\cdot k} r\left(t-k+\frac{j}{n},\frac{1}{n}\right)^2$$

$$RV(t,k,n) \to^{p} IV(t,k) \quad \text{as} \quad n\to\infty$$

where n is the sampling frequency of 33 intervals per day when we derive the daily RV.

4.2. Integrated volatility and jumps

When we allow for discrete jumps, the returns on futures at time t over the interval $[t-k, t]$ can be decomposed as

$$r(t,k) = \ln F_t - \ln F_{t-k} = \int_{t-k}^{t} \mu(\tau)d\tau + \int_{t-k}^{t} \sigma(\tau)dW_\tau + \int_{t-k}^{t} x(\tau)dN(\lambda\tau).$$