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Oil and stock market volatility: A multivariate stochastic volatility perspective

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ABSTRACT

This paper models the volatility of stock and oil futures markets using the multivariate stochastic volatility structure in an attempt to extract information intertwined in both markets for risk prediction. It offers four major findings. First, the stock and oil futures prices are inter-related. Their correlation follows a time-varying dynamic process and tends to increase when the markets are more volatile. Second, conditioned on the past information, the volatility in each market is very persistent, i.e., it varies in a predictable manner. Third, there is inter-market dependence in volatility. Innovations that hit either market can affect the volatility in the other market. In other words, conditioned on the persistence and the past volatility in their respective markets, the past volatility of the stock (oil futures) market also has predictive power over the future volatility of the oil futures (stock) market. Finally, the model produces more accurate Value-at-Risk estimates than other benchmarks commonly used in the financial industry.

1. Introduction

Oil is one of the most important production factors in an economy. Not surprisingly, a growing theoretical and empirical literature has been devoted to the study of oil and its impact on the economy. Rising oil prices lead to higher production costs which affect inflation, consumer confidence and therefore economic growth. Several studies report a clear negative correlation between energy prices and aggregate output or employment. For instance, Hamilton (1983) and Gisser and Goodwin (1986) demonstrate that rising oil prices are responsible for recessions. Rotemberg and Woodford (1996) estimate that a 10% increase in oil prices leads to an average GDP decline of 2.5% five or six quarters later. Jones et al. (2004) estimate that the oil price–GDP elasticity (the ratio of percentage change in GDP to percentage change in oil price) is around −0.06. However, Lee et al. (1996), Hamilton (1996), Huntington (1998), among others, report an asymmetric relationship between oil prices and the macroeconomy. Rising oil prices seem to decrease the aggregate economic activities more than falling oil prices stimulate them. Furthermore, Bernanke (1983) and Pindyck (1991) show that large oil price movements increase uncertainty about future prices and thus cause delays in business investments. Nevertheless, Hooker (1996) indicates that the correlation between oil prices and economic activity appears to be much weaker in data since 1985, so the suggestion that oil shocks contribute directly to the economic downturn remains controversial.

The connection between oil and stock prices appears to be quite natural. Theoretically, the value of a firm is the present value of expected future cash flows. Rising oil prices affect the future cash flows of a firm, either negatively or positively depending on whether the firm is producing or consuming oil. In addition, oil prices also affect interest rates in the economy via inflation and monetary policy of the central bank. Rising oil prices lead to high inflation which increases interest rates. Furthermore, the central bank often uses contractionary monetary policy to fight inflation. This further increases interest rates. As a result, the discount rate of the firm also increases. Increasing discount rate leads to lower stock price, other things equal. Empirical findings, however, are mixed. Jones and Kaul (1996) find that there is an adverse impact of oil prices on stock prices in the U.S., Canada, the U.K., and Japan in the period 1947–1991. Papapetrou (2001) shows that rising oil prices tend to reduce the real stock returns in Greece. At the industry level, Faff and Brailsford (1999), Sadorsky (2001) find that there is positive impact of oil prices on stock returns of oil and gas companies. However, El-Sharif et al. (2005) show that the impact of oil prices on non-oil and gas sectors is very weak. Huang et al. (1996) find that oil shocks do not have any impact on the aggregate stock market.

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The link between the oil and stock markets appears not only in return but also in volatility. Clark (1973), Tauchen and Pitts (1983), and Ross (1989) note that it is the volatility of an asset, not its return, that is related to the rate of information flow to a market. Thus, volatility is a good measure of information flow among markets. Exploring information flow may generate new insights. For instance, this study discovers a bidirectional dependence in volatility between stock and oil markets. That is, shocks to either market help predict not only volatility in their own market but also that in the other market.

This paper attempts to extract information intertwined in stock and oil prices. It will not focus on the relationship between stock and oil returns, which many papers cited above have studied, but aims more at volatility models that can extract useful information and information flow with good forecasting power. Modeling and forecasting volatility are very important for at least two reasons. First, volatility is an important variable for pricing derivatives, whose trading volume has quadrupled in recent years. Furthermore, volatility is an important input in risk management. For instance, it is used to construct optimal hedge ratios to hedge against risk and to estimate the value at risk, to name only two. Second, in making efficient econometric inference about the mean of a variable, we need a correct specification of its volatility.

There is growing literature investigating the stochastic volatility of oil prices. Agnolucci (2009) shows that GARCH-type models forecast oil volatility better than the implied volatility obtained from inverting the Black–Scholes equation. Wei et al. (2010) find that the non-linear GARCH-type models which account for long-memory and asymmetric volatility perform better than the linear counterparts in forecasting over long horizon. Sadorsky (2006) reports that the GARCH(1,1) model outperforms more complex models, such as state space, vector autoregression, bivariate GARCH(1,1). Fong and See (2002) and Vo (2009) show that the forecasting power of GARCH and stochastic volatility models will improve if the structural breaks of the time series are taken into account. This paper differs from those studies in that it attempts to model the volatility interaction between the stock and oil markets to extract the information in one market that has not yet been incorporated into the other market in order to improve the forecasting power of volatility models. I find that doing so will improve the forecasting power of the model.

Based on a preliminary analysis of the data, I posit a bivariate model of vector of autoregression VAR(1) with stochastic volatility (SV) for the joint processes governing the returns of the Standard and Poor's 500 (S&P 500) stock index and the oil futures. I consider two variants of the model: constant correlation and time-varying correlation. For a comprehensive discussion of multivariate stochastic volatility model, the reader is referred to Asai et al. (2006). Estimating SV-type models is a challenge. Besides the inherent issues of multivariate models, such as high dimensions of parameter space and the requirement for positive semi-definiteness of the covariance matrix, these models do not have closed-form likelihood function due to their latent structure of the variance. Thus, the maximum likelihood method cannot be used directly. Several estimation methods have been proposed in the literature, including GMM by Melino and Turnbull (1990), and Sorensen (2000), the quasi-maximum likelihood of Harvey et al. (1994), the indirect inference of Gourieroux et al. (1993), the efficient method of moments by Gallant et al. (1997), the simulated maximum likelihood by Danielsson (1994), Durbin and Koopman (1997), and Sandmann and Koopman (1998), and the Bayesian Markov Chain Monte Carlo (MCMC) method by Jacquier et al. (1994), and Kim et al. (1998). However, Andersen et al. (1999) show that MCMC is one of the most efficient methods. Therefore, this paper uses the Bayesian MCMC method to estimate the models. To compare models in terms of goodness-of-fit, I use the deviance information criterion (DIC) of Spiegelhalter et al. (2002) which is a generalization of the popular Akaike information criterion (AIC) for complex hierarchical models.

The empirical results of the paper offer four major findings. First, there is evidence that the correlation between the stock and oil markets is not constant but time-varying. It tends to increase with the volatility in the market. Second, the daily volatility in each market is very persistent. That is, it varies over time in a predictable manner, conditioned on the past volatilities. Third, there is a bidirectional dependence in volatility between the two markets. Innovations that hit either market can affect the volatility in the other market. In other words, conditioned on the persistence and the past volatility in their own markets, the past volatility of the stock (oil) market also has predictive power over the future volatility of the oil (stock) market. Finally, in validating the informativeness of the model by conducting a Value-at-Risk (VaR) analysis on the stock market, I find that the model performs much better than benchmark methods commonly used in the financial industry in producing the value at risk estimates.

The remainder of the paper is organized as follows. Section 2 describes the data set and the preliminary analysis. Section 3 discusses the models used in the paper. Section 4 discusses the estimation methodology and presents the empirical results. The VaR analysis is conducted in Section 5. Section 6 concludes the paper.

2. Data and preliminary analysis

The data set used in this study consists of a daily oil price time series and a daily broad market index, S&P 500, time series. Both series span from January 06, 1999 to July 26, 2009. The dataset is divided into two parts. The first one, from January 06, 1999 to December 31, 2008, is for model estimation. The remainder is for forecasting assessment. The oil time series is a daily oil futures price series of the West Texas Intermediate (WTI) crude oil futures contract traded on the New York Mercantile Exchange. The contract is denominated in 1000 U.S. barrels (42,000 gal) of light sweet oil. It is obtained from the historical database of the U.S. Department of Energy. The S&P 500 stock index series is obtained from the Yahoo Finance database. For both series, daily returns, in percentage, are defined as $r_t = 100[ln(p_t) - \ln(p_{t-1})]$.

Table 1 presents some descriptive statistics for both returns time series. Both return series have small means. For each one, the standard deviation is much greater than the mean in absolute value, indicating that the mean is not significantly different from zero. Both series are slightly skewed to the left. Their excess kurtosis is significantly positive, indicating that they have heavy tails relative to the normal distribution. Both Kolmogorov–Smirnov and Jarque–Bera tests reject the null hypothesis that the return distributions are normal. Ljung–Box portmanteau tests on return and squared return series at 6 and 12 lags indicate a high serial correlation in the first and second moments. Furthermore, the *ARCH* tests at 1, 6 and 12 lags reject the null hypothesis of homoscedasticity in the data.

Fig. 1 graphs the S&P 500 stock index, its return and the return distribution. We observe that the return displays volatility clustering.

Table 1
Descriptive statistics for return series.

Statistics	Oil futures	S&P 500
Mean (%)	.07	−.01
Std. dev. (%)	2.62	1.40
Skewness	−.22	−.10
Excess kurtosis	3.80	7.37
Kolmogorov–Smirnov	.047*	.079*
Jarque–Bera	1616.96*	5988.52*
ARCH(1)	36.74*	4.39*
ARCH(6)	53.95*	64.21*
ARCH(12)	68.55*	82.74*
Ljung–Box (6)	25.61*	43.33*
Ljung–Box (12)	31.73*	64.78*
Ljung–Box (6) on squared returns	543.16*	1327.48*
Ljung–Box (12) on squared returns	889.38*	2758.74*

* Significant at the 5% level.