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Forecasting crude oil market volatility: A Markov switching multifractal volatility approach

Yudong Wang[a,*], Chongfeng Wu[b], Li Yang[c]

[a] School of Economics and Management, Nanjing University of Science and Technology, China
[b] Antai College of Economics & Management, Shanghai Jiao Tong University, China
[c] School of Banking and Finance, University of New South Wales, Australia

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ABSTRACT

We use a Markov switching multifractal (MSM) volatility model to forecast crude oil return volatility. Not only can the model capture stylized facts of multiscaling, long memory, and structural breaks in volatility, it is also more parsimonious in parameterization, after allowing for hundreds of regimes in the volatility. Our in-sample results suggest that MSM models fit oil return data better than the traditional GARCH-class models. The out-of-sample results show that MSM models generate more accurate volatility forecasts than either popular GARCH-class models or the historical volatility model.

1. Introduction

In recent years, large fluctuations in crude oil prices have caused grave concern among both market participants and regulators. One of the reasons for this concern is that the oil price uncertainty has a significant impact on the economy (Elder & Serletis, 2010). Theories of both investment under uncertainty and real options predict that an uncertainty about oil prices can depress current investment (Bernanke, 1983; Brennan & Schwartz, 1985; Henry, 1974; Majd & Pindyck, 1987). In addition, the volatility is a key input in pricing options and a major determinant of the value at risk (VaR). Therefore, the modeling and forecasting of the crude oil return volatility are of considerable interest among academics.

In the literature on the forecasting of volatility, the family of generalized autoregressive conditional heteroscedasticity (GARCH) models (Bollerslev, 1986) has been used widely for capturing the dynamics of oil return volatility (see for example Alizadeh, Nomikos, & Pouliasis, 2008; Giot & Laurent, 2003; Kang, Kang, & Yoon, 2009; Mohammadi & Su, 2010; Narayan & Narayan, 2007; Nomikos & Pouliasis, 2011; Sadorsky, 2006; Wang & Wu, 2012; Wei, Wang, & Huang, 2010). However, several shortcomings of GARCH-class models have been observed. First, most GARCH-class models can only capture the characteristic of short memory, rather than long-range dependence, even though long-range dependence in volatility has been documented commonly in the literature. The fractional integrated GARCH (FIGARCH) of Baillie, Bollerslev, and Mikkelsen (1996) and its extensions seem to capture the long memory in volatility well. However, the unanimous finding of hyperbolic decay of the autocorrelation function of absolute returns or squared returns is more likely to be a fiction due to unaccounted structural breaks, rather than the “genuine” one revealed by FIGARCH. Lamoureux and Lastrapes (1990) argue that the persistence implied by GARCH models becomes much weaker following the incorporation of structural breaks. Specifically, Lee, Hu, and Chiou (2010) show empirically that some sudden events (e.g., the Iraqi invasion of Kuwait and the Gulf Wars) result in an

* Correspondence to: XiaoLinwei Street 200, Xuanwu District, Nanjing, China. Tel.: +86 13681663442.
E-mail addresses: wangyudongnj@126.com (Y. Wang), cfwu@sjtu.edu.cn (C. Wu), l.yang@unsw.edu.au (L. Yang).

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increase in the permanent component of the conditional variance, which is evidence of structural breaks. The simple regime switching process can capture structural shifts in the volatility well, but can also lead to the spurious finding of fractional integration (Granger & Terasvirta, 1999) and exponential rather than hyperbolic decay of the autocorrelation function (Ryden, Terasvirta, & Asbrink, 1998). Baillie and Morana (2009) claim that the proposed adaptive FIGARCH (AFIGARCH) incorporates both long memory and structural breaks by allowing the intercept of FIGARCH to follow a slowly varying function specified by Gallant's (1984) flexible functional form. As was pointed out by Wang, Bauwens, and Hsiao (2013), this parametric model is less efficient if there are no structural breaks in the sample period. In addition, the AFIGARCH model has the problem of needing to determine the order of the trigonometric terms in the Gallant flexible functional form, in addition to the order of the specification of the stationary components in the conditional variance equation. For larger values of the order of the trigonometric terms, the AFIGARCH model has more parameters that need to be estimated, and hence is more likely to result in over-fitting, where a model includes irrelevant explanatory variables that may improve the in-sample fitting but cause a poorer out-of-sample performance.

Second, GARCH-class models cannot accommodate the property of multiscaling (or multifractality) (Lux & Kaizoji, 2007), which is a well-known stylized fact in economic data (Cont, 2001). The scaling property, which is a concept borrowed from statistical physics, defines the behaviors of some forms of volatility measures (e.g., the squared or absolute returns) as a function of the time interval on which the returns are computed.[1] The scaling behavior is characterized by the so-called Hurst exponent and its related index. If q-order moments of the distributions of price increments display different scaling behaviors for different values of q, a multiscaling behavior is revealed. The investigation of scaling behaviors in economic and financial data has expanded considerably since the work of Mandelbrot (1963) (see for example Mandelbrot, 1997, 2001; Mantegna & Stanley, 1995; Muller et al., 1990; Stanley & Plerou, 2001). Multiscaling in crude oil markets, which is what we are interested in, is also found in a few studies (Alvarez-Ramirez, Alvarez, & Rodriguez, 2008; Wang & Liu, 2010; Wang & Wu, 2013). Traditional GARCH-class models are always related to the dynamics of squared returns rather than to another order of moments, and therefore, they do not take into account multiscaling behavior in price movements. The recent empirical study by Wang, Wei, and Wu (2011) also shows the lack of ability of GARCH-class models to capture multiscaling volatility in crude oil markets.

In this paper, we use the Markov switching multifractal (MSM) model of Calvet and Fisher (2001) to forecast the crude oil market volatility. This model is motivated by the stylized fact of multiscaling behavior or multifractality in financial data. The MSM model assumes a hierarchical and multiplicative structure of heterogeneous volatility components, which differs fundamentally from conventional volatility models (such as GARCH-class ones) (Lux & Kaizoji, 2007). The advantage of a MSM model over the conventional regime-switching model is that, while the number of parameters grows quadratically as the number of states increases in a regime-switching model, the MSM model is more parsimonious in parameterization, even after allowing for hundreds of states in order to capture possible structural changes. The MSM model is known to generate outliers and long memory in the volatility and to decompose the volatility into components with heterogeneous decay rates (Calvet & Fisher, 2004). Therefore, it can address the aforementioned problems of traditional volatility models well.

We apply the MSM model to West Texas Intermediate (WTI) and Brent crude oil return data. We compare its in-sample and out-of-sample performances with those of several traditional models, including the popular GARCH-class models and the historical volatility (HV) model. Our in-sample results based on Vuong's (1989) closeness test suggest that MSM models fit the data significantly better than GARCH-class models. For the comparison of out-of-sample performances, we use six loss functions to evaluate the forecast accuracy. An advanced econometric test named the model confidence set (MCS; see Hansen, Lunde, & Nason, 2011) is employed to examine further whether the differences in forecasting losses among different models are statistically significant. We find that MSM models produce more accurate forecasts than either GARCH-class models or the HV model for most of the loss functions employed. The GARCH and HV models are always excluded from MCS at the 90% confidence level, while the MSM models are included in MCS under most loss criteria. Based on the empirical evidence, we conclude that the MSM models outperform the GARCH-class models for forecasting the crude oil market volatility.

The remainder of this paper is organized as follows. Section 2 provides a general description of MSM models for forecasting the volatility. Section 3 describes the data and provides some preliminary analysis. Section 4 reports the empirical results, and Section 5 concludes.

2. Forecasting models

2.1. Markov switching multifractal (MSM) volatility model

We forecast the crude oil return volatility using the MSM volatility model introduced by Calvet and Fisher (2001). The MSM volatility model assumes that the underlying return follows a discrete-time Markov process with multifrequency stochastic volatility.[2]

We denote by ε_t the innovations of crude oil returns, r_t, which can be expressed as $r_t = \mu_t + \varepsilon_t$, where μ_t is the conditional mean. MSM models the innovations ε_t in the

[1] There is also another type of scaling behavior that is studied in the economics literature: the behavior of the tails of the distribution of returns as a function of the size of the price changes, but the interval on which the returns are measured is constant. This type of scaling behavior is measured by a tail index of the distribution.

[2] We use the ML estimator of the MSM model. For a detailed presentation of the ML estimator, see Calvet and Fisher (2004).