Energy Policy 71 (2014) 76–93

Contents lists available at ScienceDirect

Energy Policy

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

True or spurious long memory in volatility: Further evidence on the energy futures markets

Lanouar Charfeddine [a,b,*]

[a] Department of Finance and Economics, College of Business and Economics, P.O. Box 2713, Doha, Qatar
[b] Institut Supérieur de Gestion de Gabès (ISGG), University of Gabès, Tunisia

HIGHLIGHTS

- This paper investigates the long memory properties of the futures energy volatility.
- We estimate a variety of GARCH-class of models.
- The Adaptative-FIGARCH(1,d,1,k) model has been used to account for both long memory and breaks.
- 5 out of the 8 futures energy series are characterized by both long memory and structural breaks.
- The 3 other series are characterized by only long range dependence in volatility.

ARTICLE INFO

Article history:
Received 31 January 2014
Received in revised form
10 April 2014
Accepted 21 April 2014
Available online 17 May 2014

Keywords:
Long memory
Structural breaks
Fractional integration
Volatility
Volatility forecasting

ABSTRACT

The main goal of this paper is to investigate whether the long memory behavior observed in many volatility energy futures markets series is a spurious behavior or not. For this purpose, we employ a wide variety of advanced volatility models that allow for long memory and/or structural changes: the GARCH (1,1), the FIGARCH(1,d,1), the Adaptative-GARCH(1,1,k), and the Adaptative-FIGARCH(1,d,1,k) models. To compare forecasting ability of these models, we use out-of-sample forecasting performance. Using the crude oil, heating oil, gasoline and propane volatility futures energy time series with 1-month and 3-month maturities, we found that five out of the eight time series are characterized by both long memory and structural breaks. For these series, dates of breaks coincide with some major economics and financial events. For the three other time series, we found strong evidence of long memory in volatility.

1. Introduction

Modeling and forecasting volatility are of great importance when pricing derivatives, calculating measures of risk, and hedging against portfolio risk. The price of almost every derivative security is affected by changes in volatility. Risk management models used by financial institutions and required by regulators consider time-varying volatility as a key input. Volatility is also an important determinant of macroeconomic conditions. Changes in energy prices are often considered to be key factors in understanding fluctuations in stock prices, real GDP growth rates, inflation, employment, and exchange rates (Hamilton, 1983, 2009, 2013; Kilian, 2009; Wang et al., 2011; Wang and Wu, 2012; Arouri et al., 2012; Ozdemir et al., 2013; Kang and Yoon, 2013; Creti et al., 2013). Moreover, outlier and extreme events, such as the Gulf War and the financial crisis, have an important impact on volatility dynamics (Wang and Wu, 2012; Arouri et al., 2012). Therefore, determining the true data generating process (DGP) of volatility dynamics is of high importance for market participants, financial analysts and policymakers. For instance, policymakers must seriously consider the fluctuation of and trends in energy prices (i.e., crude oil and heating oil), as they are both inputs into production and consumer goods (Hamilton, 1983; Masih et al., 2011). Market participants and financial analysts should understand the origins of energy shocks because each shock may require specific portfolio adjustments (Kilian and Park, 2009).

In the empirical finance literature, a growing number of studies have analyzed modeling and forecasting volatility. Many empirical studies have examined the volatility time series by supposing that the DGP of volatility series is characterized by sudden changes in the volatility (Hamilton and Susmel, 1994; Gray, 1996; Klassen, 2002; Marcucci, 2005; Baillie and Morana, 2009). Hamilton and

* Tel.: +966 5 46 35 29 35.
E-mail address: lanouar_charf@yahoo.fr

http://dx.doi.org/10.1016/j.enpol.2014.04.027
0301-4215/

Susmel (1994) and Susmel (2000) have developed the Markov switching regime model with an ARCH(q) process under each regime (SWARCH) model. Marcucci (2005) proposed the Regime-Switching GARCH (MRS-GARCH) models, where the parameters are allowed to switch between a low and a high volatility regime as in Gray (1996) and Klassen (2002). Recently, Baillie and Morana (2009) have introduced the so-called adaptative GARCH (A-GARCH) model, which enables structural changes in the conditional variance. In the A-GARCH model, the variance intercept switches between regimes according to Gallant (1984)'s smooth flexible functional form.

Recent studies suggested that shocks on volatility have long-lasting effects. This behavior is known in the empirical finance literature as long-range dependence behavior or long memory behavior. Long memory in volatility occurs when the effects of volatility shocks decrease slowly. This behavior is observed on the autocorrelation function, which decays slowly to zero, or on the spectral density, which diverges to infinity at a frequency near zero. Long memory behavior in volatility has been observed in several financial time series; see, for instance, Ding et al. (1993), Dacorogna et al. (1993), Baillie et al. (1996), Breidt et al. (1998) and Harvey (1998). In these cases, volatility can be modeled using a fractionally integrated model, such as the Fractionally Integrated GARCH (FIGARCH) model or the Fractionally Integrated Exponential GARCH (FIEGARCH) model. One of the most compelling motivations regarding the importance of long memory is that it implies long-run effects of shocks compared to conventional macroeconomic approaches. Moreover, the evidence of long memory in return is synonymous with the presence of non-linear dependence between observations, which means that it is possible to predict future returns based on historical data. This latter result is of great importance, as it is in total contradiction to the weak-form efficiency hypothesis of energy markets.

An important issue that arises when modeling the volatility of futures energy prices using long memory processes is the fact that various types of structural change models can produce a high persistence of volatility (Charfeddine and Guegan, 2012; Baillie and Morana, 2009; Beltratti and Morana, 2006). For instance, short memory models with a changing regime in the mean or volatility can generate behavior identical to the one derived from a long memory process when looking at autocovariance function and spectral density. This behavior has been noted by many authors and has been identified in several processes such as the mean-plus-noise model of Chen and Tiao (1990), the stochastic permanent break model of Engel and Smith (1999), the sign model of Granger and Terasvirta (1999) and the infrequent break model of Gourieroux and Jasiak (2001). To the best of our knowledge, there is no formal test that can differentiate between true and spurious long memory in the theoretical and empirical literature. Thus, discriminating between these two types of behavior remains a challenging and important task from two perspectives. Regarding economics, financial shocks are known to have a long-lasting effect when the data generating process (DGP) is a true long memory process. However, when the DGP is a model with a short memory between breaks, the autocorrelations should theoretically decline exponentially, and the impact of shocks is expected to die out subsequently after a small number of observations. Regarding statistics, inferences under a stationary long memory model are notably different than those under a short memory model with structural breaks. However, estimating a long memory parameter without considering the presence of breaks in the data sets may lead to a misspecification and hence to overestimating the true parameter.

In this paper, our primary purpose is to examine the long memory properties of the futures energy prices volatility series. In particular, we investigate whether the observed long memory behavior in the volatility futures energy is a true behavior or a spurious behavior created by structural breaks. To this end, we estimate different structural breaks and/or long memory processes for each energy futures time series. For energy futures time series, we use crude oil, gasoline, heating oil and propane in 1-month and 3-month maturities. Our paper differs from earlier studies on modeling energy prices volatility in three ways. First, in addition to the modified rescaled range statistic (R/S) of Lo (1991) and the Gaussian Semiparametric (GSP) method of Robinson and Henry (1999) largely used in the empirical literature, we employ the detrended fluctuation analysis (DFA) method of Peng et al. (1994) and the two-step feasible exact local whittle (2FELW) of Shimotsu (2010). This approach provides additional information concerning the robustness of long-memory inference on daily futures energy price volatilities. Second, in contrast to earlier studies that rely on testing for long-range dependence without considering structural breaks, or only by estimating the long memory parameter "d" in non-overlapping sub-samples where dates of breaks are exogenously determined, in this paper, we estimate the long memory parameter and the date of breaks simultaneously using the Adaptative FIGARCH (A-FIGARCH) model proposed recently by Baillie and Morana (2009). Third, we compare the GARCH(1,1), A-GARCH(1,1,k), FIGARCH(1,d,1), and A-FIGARCH(1,d,1,k) models in terms of their ability to describe the behavior of conditional variance using out-of-sample forecast evaluations.

The paper is structured as follows. In Section 2, we provide a review of the literature on the dynamics of the volatility of futures energy markets. In Section 3, we describe tests of structural changes in volatility, long memory estimation methods, GARCH-class of models and the out-of-sample testing framework. In Section 4, we present and discuss empirical results. Finally, Section 5 presents a summary and policy implications.

2. Literature review

As noted earlier, determining the stochastic properties of the volatility of energy prices is important when forecasting, hedging, planning and making decisions regarding capital investment and portfolio diversification. In recent years, there is a growing consensus among researchers that the futures energy prices volatility can be better described by nonlinear econometric models such as long range dependence and structural breaks models (see for instance Baillie et al., 2007; Elder and Serletis, 2008; Fernandez, 2010; Wang and Wu, 2012; Arouri et al., 2012; Ozdemir et al., 2013; Kang and Yoon, 2013). Empirical evidence about the true data generating process of the futures energy time series can be classified into three major categories.

The first category of studies has examined the hypothesis that shocks on the volatility of the futures energy contracts have long-lasting effects. This behavior is known in the empirical finance literature as long-range dependence behavior. For instance, Baillie et al. (2007) have investigated the properties of long memory in volatility of both daily and high frequency intraday futures returns for six important commodities. They found that the volatility processes are very well described by FIGARCH models, with statistically significant long memory parameter estimates. They suggest that long memory in volatility is a pervasive and consistent feature of commodity returns and is not just being caused by shocks or regime shifts to the underlying price processes. This latter result is confirmed by that obtained by Cunado et al. (2010) when investigating long range dependence behavior for several energy futures markets and for different contracts maturity. They found strong evidence of long memory in volatility. In contrast to this evidence of the presence of a stationary long memory behavior in futures energy contracts, Elder and Serletis (2008)