



A metric and topological analysis of determinism in the crude oil spot market

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ARTICLE INFO

Article history:

Received 21 May 2011

Received in revised form 29 September 2011

Accepted 1 October 2011

Available online 10 October 2011

Keywords:

Nonlinear dynamics

Chaos

Correlation dimension

Lyapunov exponents

Recurrence plots

ABSTRACT

We test whether the spot price of crude oil is determined by stochastic rules or exhibits deterministic endogenous fluctuations. In our analysis, we employ both metric (correlation dimension and Lyapunov exponents) and topological (recurrence plots) diagnostic tools for chaotic dynamics. We find that the underlying system for crude oil spot prices (i) is of high dimensionality (no stabilization of the correlation dimension), (ii) does not exhibit sensitive dependence on initial conditions, and (iii) is not characterized by the recurrence property. Thus, the empirical evidence suggests that stochastic rather than deterministic rules are present in the system dynamics of the crude oil spot market. Recurrent plot analysis indicates that volatility clustering is an adequate, but not complete, explanation of the morphology of oil spot prices.

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1. Introduction

In this study, we research the issue of deterministic chaos in crude oil spot prices employing both metric and topological diagnostics. Chaos refers to bounded steady-state behavior that is not an equilibrium point, not quasi-periodic, and not periodic. Certain parameterizations of nonlinear difference equations or systems of at least three nonlinear differential equations can produce chaotic behavior. Sensitive dependence on initial conditions is the distinctive feature of chaotic dynamical systems. This property means that nearby points become exponentially separated in finite time (repelling trajectories), which makes the evolution of those systems very complex and essentially random by standard statistical tests. Combined with measurement limitations of the current (initial) state, sensitive dependence places an upper bound on the ability to forecast chaotic systems, even if the model is known with certainty. Predictability (ordered motion) is possible only on short time scales.

In search of a deeper understanding of the underlying laws of motion, chaotic dynamical analysis has extensively been applied in economic and financial systems. The concepts of self-generating dynamically complex structures and limited forecasting ability have a strong appeal for financial behavior. For review of theoretical modeling and empirical applications of chaos and complex dynamics in economics and finance, see Baumol and Benhabib (1989), LeBaron (1994), and Puu (2000), to mention a few.

Crude oil is the world's most actively traded commodity in both volume and value. A significant academic literature points to the importance of oil prices for economic activity as large and protracted increases in the price of oil have been typically associated with sharp downturns in economic activity and high inflation (see Hamilton (1983, 2008) and IEA (2004), among others).¹ Recently, a number of insights are provided in the special issue of *Macroeconomic Dynamics* (2011) on oil price shocks. For instance, some of the main results include (Serletis and Elder, 2011): (i) the presence of nonlinearity in the oil price–output prediction regression and response function, (ii) the presence of significant effects of oil price uncertainty (volatility) on the level of economic activity (consistent with the predictions of real options theory), and (iii) the significant influence of oil price shocks on the probability of entering a recession. Sadorsky (2003) finds that oil price volatility has a significant impact on stock price volatility. In recent years, the emergence of oil stabilization funds, as the largest category of sovereign wealth funds, is also indicative of the importance of oil prices for economic activity.² Oil prices are now recognized as the primary source of macroeconomic risk for a large number of countries (Poghosyan and Hesse, 2009) underscoring the need for understanding the oil price dynamics.³

The recent volatility in oil prices has also coincided with the dominance of upstream and downstream cartels or oligopolies. It has been

¹ For example, world GDP would be at least half of 1% lower—equivalent to \$255 billion—in the year following a \$10 oil price increase according to an IEA report (2004).

² See Abu Dhabi's Investment Authority (ADIA) at \$627 billion, Norway's Global Pension Fund (GPF) at \$443 billion, Saudi Arabia's Foreign Holdings (SAMA) at \$415 billion, and China's Investment Company (SAFE) at \$347 billion, to name a few.

³ Over the past five years oil prices have gone up and down by more than \$60.

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argued that global oil prices do not always behave as predicted by conventional supply and demand theory. In addition to cyclical factors, researchers have hinted to structural factors as primary drivers. More specifically, the two main structural contributors to volatility have been (i) the falling spare capacity in refining and transportation and (ii) the emergence of a new class of investors (particularly pension funds) that rely on derivative products on oil prices to diversify their portfolios (Haigh et al., 2005; Kogan et al., 2006).⁴ Xu (2010) notes that “... adding crude oil with equities into a diversified portfolio can provide superior portfolio performance compared with equities alone.” A better understanding of the true nature of oil price changes has important implications for decision makers as they formulate macroeconomic policy, engage in portfolio construction and hedging decisions or decisions to invest in physical infrastructure in the oil industry. Hence the dynamical evolution of oil prices has important business implications and plays a key role in risk management.

The empirical detection of a strange attractor in oil spot prices tends to be inconclusive in the literature.⁵ Using correlation dimension, entropy, and Lyapunov exponent estimates, Panas and Ninni (2000) report evidence in support of deterministic chaos for a number of oil products in the Rotterdam and Mediterranean petroleum markets. Adrangi et al. (2001) find evidence inconsistent with deterministic structure in oil futures prices based on correlation dimension and entropy estimates. Moshiri and Foroutan (2006) find positive evidence of chaos in oil futures prices based on correlation dimension but negative evidence based on Lyapunov exponents. Matilla-Garcia (2007) reports evidence in support of deterministic dynamics using a stability test of largest Lyapunov exponent.⁶

We analyze the issue of deterministic structure in oil spot prices by applying both metric and topological methodologies. Previous research has primarily focused on metric-based tests for chaos. Our data set consists of daily oil spot prices covering the period 1/2/1985–8/31/2011. The metric methodologies applied are the correlation dimension and Lyapunov exponents. We additionally employ recurrence plot (RP) analysis, which is based on the topological approach to studying nonlinear complex dynamics. The important distinction and advantage of the topological approach to chaos is that, unlike the metric approach, it preserves the time-ordering information in the time series in addition to the spatial structure. It attempts to detect the more fundamental property of a chaotic system, the recurrence of states. RP analysis can be quite powerful in the detection of chaos as it is robust to data set limitations, such as small, noisy data sets, which are common in economics and finance. This study therefore contributes to an overall picture of the role of chaos in the oil market. Thus we define a working hypothesis that addresses three important features of chaotic signals, namely, the existence of a low-dimensional attractor in the underlying dynamics, the presence of sensitive dependence on initial conditions, and the manifestation of the recurrence property. The test results from both metric and topological methodologies suggest that oil spot prices are the measured footprint of a stochastic rather than a deterministic system. Recurrence plot analysis suggests that volatility clustering explains the variable morphology of oil prices largely, but not entirely.

⁴ Speculative forces have a greater effect on cartel prices, as in the oil market, rather than competitive prices (Adelman, 2004).

⁵ Lichtenberg and Ujihara (1989) formulate a nonlinear cobweb model to show that the price time series may exhibit chaotic behavior and apply it to the U.S. crude oil market.

⁶ In other energy markets, Chwee (1998) and Serletis and Gogas (1999) find that natural gas futures and North American natural gas liquid markets are characterized by chaotic tendencies. Adrangi et al. (2001) do not find chaotic dynamics in heating oil and unleaded gasoline futures prices. Matilla-Garcia (2007) report deterministic structure in natural gas and unleaded gasoline futures prices. Testing for nonlinear dynamics in other commodity prices, see Blank (1991) for soybean futures, DeCoster et al. (1992) for sugar, silver, copper, and copper futures, and Yang and Brorsen (1993) for several futures markets.

The plan of the paper is as follows. Section 2 describes deterministic chaos and the metric- and topology-based diagnostics for its presence. In Section 3, we describe the data and present estimates of three diagnostic tests for chaos: correlation dimension, which measures the fractal dimension of the system, Lyapunov exponents, which measure the divergence rate, and RP analysis, which measures the recurrence of states of the underlying system. We conclude in Section 4 with a summary of our results.

2. Deterministic chaos

Following Mayfield and Mizrach (1992), we analyze discrete-time autonomous dynamical systems of the form

$$x_t = F(x_{t-1}), x \in R^n \tag{1}$$

where $F:U \rightarrow R^n$ with U an open subset of R^n . A closed invariant set $A \subset U$ is an attracting limit set for (1) if there exists an open neighborhood V of A such that the limit set of iterates in (1) is A for all $x \in V$ as $t \rightarrow \infty$.

What is often empirically observed is a series of scalar observations y_t , which is the measured footprint of the multidimensional system in Eq. (1). The question is how to recover the system dynamics (original trajectory) by analyzing the observational time series y_t . This is accomplished through the Takens's (1980, 1983) embedding theorem. Define an m – dimensional vector constructed from the observed time series

$$y_t^m = (y_t, \dots, y_{t+m-1}) = (g(x_t), \dots, g(F^{m-1}(x_t))) \equiv I_m, \tag{2}$$

where F^{m-1} is the composition of F with itself $m-1$ times. The idea is to reconstruct the state space by expanding the one-dimensional signal y_t into an m – dimensional phase space, where one substitutes each observation in the signal y_t with the vector y_t^m in Eq. (2). Given that the true system that generated the time series is n – dimensional, Taken's embedding theorem states that for smooth pairs (g, F) the map $I_m:R^n \rightarrow R^m$ will be an embedding for $m \geq 2n + 1$. Thus Taken's theorem guarantees the existence of diffeomorphism between the original and reconstructed attractor if the embedding dimension is sufficiently large with respect to the dimension of the strange attractor.

2.1. Correlation dimension

One important characteristic of a chaotic attractor is its dimension, which is a lower bound on the number of state variables (degrees of freedom) needed to describe the steady-state behavior. To estimate the dimension of the reconstructed attractor we use the Grassberger and Procaccia (GP: 1983, 1984) algorithm, which makes use of the idea of the correlation integral.⁷ Given the sequence of m – histories of the time series defined in Eq. (2), the correlation integral measures the number of vectors within an ϵ distance from one another and is given by

$$C_m(\epsilon) = \lim_{N \rightarrow \infty} \frac{1}{N^2} \times \#\{(i, k) \mid \|y_i^m - y_k^m\| < \epsilon\}, \quad m = 2, 3, \dots, \tag{3}$$

where $\{\Lambda\}$, $\|\cdot\|$, N , and m denote the cardinality of the set Λ , some norm, the number of m histories, and the embedding dimension, respectively. As GP showed with $\epsilon \rightarrow 0$, $C_m(\epsilon) \sim \epsilon^v$, where v is the correlation exponent. Therefore for small ϵ ,

$$\ln_2 C_m(\epsilon) = \ln_2 S + v \ln_2 \epsilon \tag{4}$$

⁷ Besides correlation dimension, other types of fractal dimension exist: the capacity or Hausdorff dimension, k – th nearest neighbor dimension, and Lyapunov dimension.

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