NONLINEAR DYNAMICS IN ENERGY FUTURES

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ABSTRACT

This paper studies the possible nonlinear and chaotic nature of three energy futures: natural gas, unleaded gasoline and light crude oil. Nonlinearity is analyzed using the generalized BDS statistic, along with Kaplan's test. The results show that nonlinearity cannot be rejected. The null hypothesis of chaos is then investigated via the stability of the largest Lyapunov exponent. Evidence of chaos is found in futures returns. Global modelling techniques, like genetic algorithms, have been used in order to estimate potential motion equations. In addition, short term forecasts in futures price movements have been conducted with these estimated equations. The results show that although forecast errors are statistically smaller than those computed with other stochastic approaches, further research on these topics needs to be done.

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1. INTRODUCTION

The behaviour of daily market energy futures can be profitable for chartists when predicting future trends as well as for analysts when explaining and determining market dynamics. Energy futures are clearly characterized by unpredictable and volatile price movements. As is well known, chaos theory shows that both characteristics are compatible with a nonlinear deterministic explanation of price movements, and not only with a pure random nonlinear approach. Despite the fact that fluctuations in prices might be attributed to some perfectly deterministic nonlinear feedback mechanism, only very short run predictions can be obtained, basically, because of the sensitivity to initial conditions that characterizes chaotic systems. If it is found that the data can be approximately described according to a nonlinear deterministic motion equation, it is worthwhile estimating it, since it might constitute a powerful forecasting tool.

Researchers in economics and finance have been interested in testing for nonlinear dependence and chaos for more than a decade now. Interest in nonlinear models has developed in parallel with an expansion in the knowledge of the properties of tools for nonlinear data analysis. Financial market data like stock market returns, exchange rate returns, natural gas futures and daily oil production have been studied, among others, by Scheinkman *et al.* (1989), Hsieh (1989), Chwee (1998) and Panas *et al.* (2000), respectively. The interest in looking for chaos on financial markets has been recently renewed (see Moshiri and Foroutan, 2006; Fernández-Rodríguez *et al*. 2005; and Shintani and Linton, 2004).

The core of this approach is that the market consists of a large number of traders who are organized into dynamic, volatile, complex, and adaptive systems that are sensitive to environmental constraints, and that evolve according to their internal structures. Daily price fluctuations are the outcome of these systems. Much research in financial economics has relied on the theory of dynamical systems to analyze price movements. This theory deals with the behaviour of the evolution of a dynamical process over time. It is realistic to assume that the equations describing the underlying futures' dynamical processes are unknown. Additionally, the researcher only observes time series of prices or returns. Fortunately, *time delay space reconstruction*, due to Takens (1981), connects time series observation data and the underlying dynamical

system. Several nonlinear techniques, based on such reconstructed space, have been developed to detect nonlinearities and chaos in observed data. Particularly, Chwee (1998) used the BDS statistic and the Lyapunov spectra to test for nonlinearity and chaos in natural gas futures. Evidence in favour of chaos was not found.

This paper analyzes the nature of three energy futures: natural gas, unleaded gasoline and light crude oil. These three futures have been intensively in terms of looking for a chaotic skeleton. As stated before results are not conclusive. The first goal of the paper is to examine the nonlinear and potential chaotic properties of these relevant energy futures. To this end several techniques are used: (1) the recent generalization of the well known BDS statistic; (2) the Kaplan statistic procedure; and (3) the stability of the largest Lyapunov exponent. The second goal of the paper is to estimate, if chaos is a potential source of nonlinearity, the motion equations driving energy futures returns. To this end genetic algorithms are used. A comparison, in terms of forecasting, with two other stochastic models is provided. This second aim is especially relevant since the available economic literature does not usually estimate the potential motion equations once chaos is detected. Obviously, in presence of nonlinear dynamics ARCH-type models are known to be very useful for forecasting. Whether these models are competitive (in terms of forecasting) in presence of nonlinear chaotic dynamics has not been investigated. Our results suggest that if the underlying process that generated observed data is chaotic, then other forecasting techniques as Genetic Algorithms outperforms (in terms of forecasting) the ARCH-type models.

The paper is organized as follows. Firstly, in section 2, the data and their basic properties, as univariate time series, are described; secondly, the generalized BDS statistic tests and the Kaplan test are presented along with their respective results for the time series under study. The third section introduces the concept of the largest Lyapunov exponent, together with a recent test for the null hypothesis of chaos. Accordingly, tests for chaos are then conducted and reported. In section 4, the estimated equations, via genetic algorithms (GA), are presented. Conclusions are provided in section 5.

2. TESTING FOR NONLINEARITY

The data consist of the following daily futures at the New York Mercantile Exchange (NYMEX): Natural Gas from 04/03/1990 to 10/19/2005 (3892 observations), Unleaded Gasoline from 03/17/1992 to 01/31/06 (3499 observations) and Light Crude Oil from 04/03/1990 to 10/19/2005 (3892). We focus, however, on market returns from these three futures prices. Stationary data sets are required when testing for nonlinearity. Returns (z_t) are defined as the difference of the logarithms of the future settlement prices $z_t^{\,i} \equiv \ln P^i_{\,t} - \ln P^i_{\,t-1}$, where $i =$ Natural Gas, Unleaded Gas and Light Crude Oil .

Table 1 presents the descriptive statistics for the three returns. In all cases, there is excess kurtosis relative to the standard distribution. The distribution of all of them is negatively skewed[2]. These observations lead us to suspect that energy futures returns are not normally distributed as is suggested by Jarque-Bera statistics.

Table 1. Summary Statistics for Energy Futures Returns

	Natural Gas	Unleaded Gas	Crude
Mean	5.35e-004	3.55e-004	2.89e-004
Standard Deviation	0.036	0.020	0.024
Skewness	-0.031	-2.34	-1.357
Kurtosis	11.334	48.06	25.289
Minimum	-0.37	-0.38	-0.40
Maximum	0.32	0.13	0.14
Jarque-Bera	1.12e+004*	2.98e+005*	8.16e+004*

Note: The Jarque-Bera statistic tests for normality and is distributed as $\chi^2(2)$. * denotes test significance at the 5% level.

Due to the fact that nonlinearity is a necessary (but not sufficient) condition for chaos, two tests for nonlinearity are conducted in this section: A generalized version of the well known BDS statistic which incorporates different time delays and so a fine search is guaranteed, and a direct test known as the Kaplan test.

2.1 Generalized BDS test

The BDS test (Brock *et al*., 1996) is used to test the null of whiteness against the alternative of nonwhite linear and nonwhite nonlinear dependence. It is based on the estimation of the correlation integral, which was introduced in the context of dynamical systems by Grassberger and Procaccia (1983).

[2] The skewness is zero for a symmetrical distribution. The kurtosis of a normal distribution is 3.

The basic idea behind state space reconstruction is that the past and the future of a time series both contain information about unobserved state variables that can be used to define a state at the present time. Reconstruction is done from a scalar time series and all relevant components (relative to the underlying dynamics) have to be extracted from it. Takens (1981) showed that this type of reconstruction yields a topologically equivalent attractor leaving the dynamic parameters invariant. The required reconstruction will embed the univariate observations into a multivariate phase space. To that end, information is encapsulated in the delay vector called the *m*-history.

The Grassberger and Procaccia correlation integral is based on Takens' 'time delay method', and it consists of the two following steps: (1) for established values of *m* (dimension) and τ (delay time), to convert the scalar time series $\{z_1, z_2, ..., z_T\}$ into a set of *m*-histories: $\mathbf{z}_i^{m,\tau} = \{z_i, z_{i+\tau}, z_{i+2\tau}, ..., z_{i+(m-1)\tau}\}$; (2) to compute the correlation function or integral which is estimated by:

$$c_{m,n}{}^{\tau}(\varepsilon) = \frac{1}{\binom{n}{2}} \sum_{i=}^{n} \sum_{j=i+1}^{n} H\left(\varepsilon - \left\| \mathbf{z}_i^{m,\tau} - \mathbf{z}_j^{m,\tau} \right\|\right) \qquad (1)$$

where $n = T-(m-1)\tau$ is the number of *m*-histories, with τ-delay time, that can be formed from *T* observations; and *H* is the Heaviside function so that $H(\mathbf{z}_i^{m,\tau}, \mathbf{z}_j^{m,\tau})$ takes the value 1 if both observations are within distance ε of each other, and 0 otherwise. In words, (1) measures the fraction of the pairs of points z_i that are within a distance of ε from each other. This distance is chosen relative to the standard deviation divided by the spread of the data.

It is known that the choice of time delay is crucial when estimating the correlation dimension (a measure based on the correlation integral), to the extent that an unfortunate time delay choice yields misleading results concerning the dimension of well known attractors. However, as Kantz and Schreiber (2004) indicate, the relevant mathematical framework for a proper choice of a time delay has not been convincingly studied.

Since the BDS test fixes τ = 1, it does not take into account all the potential power of Takens' 'time delay method' which implies a connection between geometric concepts (such as dimensions) and the analysis of time series. The 'time delay method' allows the

reconstruction of phase space. By fixing $\tau = 1$, *m* successive observations are stacked in producing the embedded phase space vectors. Real-world time series are, however, noisy and finite. These restrictions make the selection of time delay crucial: For very small τ, the coordinates of each reconstructed state, **z,** do not significantly differ from one another and therefore the points are scattered along the diagonal. As a consequence, the dynamics in the space state, that take place in the coordinates of the reconstructed space, are almost linearly dependent (which is not the case for the real observable of a nonlinear system). On the other hand, a large delay time will cause the coordinates to disjoin by stretching and folding, so this will lead to vectors whose components are (seemingly) randomly distributed in the embedding space.

Recently, a new test called BDS-G (Matilla *et al*., 2004) has included time delay as a new parameter, and in this light, the well known BDS is interpreted as a particular case of the BDS-G test.

The BDS-G statistic:

$$BDSG(m,T,\varepsilon,\tau) = \sqrt{T-(m-1)\tau}\ \frac{c^{\tau}{}_{m,n}(\varepsilon) - (c_1(\varepsilon))^m}{\sigma^{\tau}{}_{m,n}(\varepsilon)}$$

has an asymptotic normal distribution under the null hypothesis of IID, with mean zero and variance one, where $\sigma^{\tau}{}_{m,n}(\varepsilon)$ is an estimate of the asymptotic standard error of $\left[c^{\tau}{}_{m,n}(\varepsilon) - (c_1(\varepsilon))^m\right]$.

The BDS and the BDS-G tests provide an important advance in testing for nonlinear dependence when applied to prewhitened data. Consequentially, both statistical tests can be used to determine whether there is evidence of dependence remaining in the data. If all linear dependence has already been removed, then any remaining dependence must be nonlinear. Still, rejection of the null of IID could result either from a nonlinear deterministic or from a nonlinear stochastic system. In order to decide between these two alternatives one has to rely on other procedures. Particularly, we rely on the stability of Lyapunov exponents, which will be explained later in this paper.

In order to compute BDS-G tests one has to choose several parameters: the time delay τ, the embedding dimension *m*, and the radius ε. In order to select the

dimensional distance ε and the embedding dimension *m*, it is advisable to follow the indications of Brock *et al*. (1991) and Kanzler (1999), who have found that the power of the BDS test is maximized when the dimensional distance is selected between 1 and 2 times the standard deviation. Moreover, Kanzler points out that as the embedding dimension *m* increases, the BDS empirical distribution moves away from its asymptotic distribution. This result holds for the BDS-G empirical distribution. Even though several methods exist to select τ, we estimate BDS-G for several time delays.

2.2 Results with BDS-G Statistic

Firstly, we proceed to apply the BDS-G statistic after linear dependencies have been removed from data sets by an AR filter. Therefore if the null is rejected, it implies that the residuals are compatible with a nonlinear underlying system. This procedure has shown to be valuable in the past (see, for example, Barnett *et al*. 1997).

As in Barnett *et al*. (1997) and following Chwee (1998), all time series have been filtered by using a LM test statistics on *q* lags where they are added until the null of 'no serial correlation' cannot be rejected at the 5 percent level[3]. Table 2 shows the selected filters for each data set, along with the Ljung-Box statistic on residuals, Q(15), and on squared residuals, Q2(15).

Table 2. AR Models for Futures Returns

	Natural Gas	Unleaded Gas	Crude
Fitted AR	2	5	5
Q (15) statistic	12,41	25,61	24,37
Q2 (15) statistic	340,78*	8,21	260,05*

Note: The lag length is chosen until the null of non serial correlation cannot be rejected with a LM test. The Ljung-Box Q(15) statistics tests on the residuals under the null of no autocorrelation. The Q2(15) statistic is the Ljung-Box test on the squared residuals. * denotes significance at the 1% level.

Practitioners of BDS and BDS-G tests usually consider different embedding dimensions. Table 3 shows BDS-G and BDS tests on filtered returns for five embedding dimensions[4]. Following Kanzler (1999) we have set[5] $\varepsilon = 1\sigma$. Time delay has varied from

[3] The same analysis has been conducted following a general-to-specific procedure in order to select the lag length, *q*. In this case, although the selected lags are different from those given in Table 2, BDS-G results are very similar to those presented in Table 3.

[4] Note that BDS = BDS-G ($\tau = 1$).

1 to 5. It is evident from Table 3 that the null of whiteness is rejected according to all computed statistics, and hence the remaining dependence is consistent with a nonlinear dynamic explanation. Similar results are found using the non filtered returns[6].

Table 3. BDS-G Tests Statistics for AR Residuals and Hinich Bispectral p-values

		Embedding Dimension (*m*)				
		2	3	4	5	6
Natural Gas	**Time delay**					
	1	11.40	15.31	18.00	20.58	23.86
	2	12.56	14.87	16.70	18.90	21.53
	3	9.47	12.13	13.71	15.63	17.63
	4	8.88	12.12	14.34	15.52	17.65
	5	10.27	13.51	15.74	18.41	20.44
Hinich Bispectral *p* -val				0.28		
Unleaded Gas	**Time delay**	2	3	4	5	6
	1	8.00	10.80	13.05	15.48	18.31
	2	7.90	10.71	12.96	15.28	18.31
	3	8.43	11.28	13.59	16.08	18.63
	4	8.12	10.85	12.77	14.66	16.90
	5	9.18	11.89	13.61	15.84	17.76
Hinich Bispectral *p* -val				0.37		
Crude	**Time delay**	2	3	4	5	6
	1	7.23	9.70	11.98	14.02	16.44
	2	9.30	11.58	14.19	16.56	19.05
	3	9.70	12.30	13.90	15.83	17.88
	4	8.27	11.00	13.11	15.21	17.81
	5	10.05	12.05	13.78	16.15	18.10
Hinich Bispectral *p* -val				0.31		

Note: The critical values are 1.645, 1.960 and 2.575 for the 10%, 5% and 1% critical values, respectively. All test statistics are significant at the 10%, 5% and 1% levels.

According to these results, it can be concluded that there is evidence of non-linearity of a general form, since BDS-G rejections might occur when the process has dependence in any moment of the distribution. Models that are nonlinear in variance but linear in mean are acknowledged to be valuable for modeling returns (Engle, 1982; Bollerslev, 1986; and Engle, 2002). Therefore, as residuals and returns are nonlinear, the Hinich bispectrum test (Hinich, 1982) is used in order to test for linearity on the conditional mean. One advantage of this test is that it is unaffected by the application of a linear filter. Our results are presented in Table 3 and, accordingly, energy returns seem to be linear in mean, but not on other moments[7]. In order to uncover a potential source

[5] Results for $\varepsilon = 0.5\sigma$ and $\varepsilon = 2\sigma$ are similar to those presented in Table 3.

[6] These results are not reported here, but they are available upon request.

[7] The same conclusion is arrived at if outliers are removed, indicating that the effects of outliers (extreme observations) are not crucial in order to obtain a conclusion about the nature of the underlying process.

of nonlinearity related with conditional variance (GARCH-type dynamics), we have estimated a GARCH (1,1) model using the same AR structure. After that, we have applied the BDS-G test to the standardized residuals of the GARCH(1,1)-filter with the following heteroskedastic variance equation:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

The parameter α is usually known as the ARCH(1) term, while β is the GARCH(1) term. The GARCH(1, 1) model is useful in detecting nonlinear patterns in variance. The difficulties in improving its performance when dealing with returns are well-known (see Hansen and Lunde, 2005). The parameter estimates of the GARCH(1, 1) models are presented in Table 4. The coefficients are positive and statistically significant in all cases. The Q2(15) statistics fail to reject the null of 'no autocorrelation' in the squared standardized residuals, indicating no residual ARCH effects.

Table 4. GARCH (1,1) Parameters Estimates and Diagnostics

Coefficients	Natural Gas	Unleaded Gas	Crude
w	0.0001	0.0001	0.0001
	(3.41)	(1.62)	(2,76)
ARCH(1)	0.230	0.35	0.071
	(5.06)	(2.27)	(5.70)
GARCH(1)	0.719	0.61	0.92
	(16.57)	(4.54)	(94.10)
Diagnostics			
Jarque-Bera	5.17+e3	6.5+e5	1.3+e3
	(0.00)	(0.00)	(0.00)
Kolmogorov-Smirnof	0.055	0.070	0.044
	(0.00)	(0.00)	(0.00)
Q(15)	8.86	17.94	22.40
	(0.88)	(0.26)	(0.31)
Q2(15)	11.96	2.24	21.91
	(0.68)	(0.99)	(0.11)

Notes: The sample periods are April 3, 1990 through October 19, 2005 (Natural Gas and Crude) and March 3, 1992 through January 31, 2006 (Unleaded Gas). The Bollerslev-Wooldrige robust standard errors are reported in parentheses. The Jarque-Bera statistic tests for normality and is distributed as $\chi^2(2)$, *p*-values in parenthesis. The Kolmogorov-Smirnof statistic tests for standard normal distribution on the standardized residuals. The Ljung-Box Q(15) statistics tests on the standardized residuals under the null of no autocorrelation, *p*-values in parenthesis. The Q2(15) statistic is the Ljung-Box test on the squared standardized residuals, *p*-values in parenthesis.

Table 5 presents the results of BDS-G tests on GARCH (1,1) standardized residuals. In clear contrast with the results given in Table 3, now the null of independence is not so generally rejected. Full rejection, that is, regardless of the

embedding dimension and the time delay, is uniquely found for the Crude residuals. However, dependences are found in the case of Natural Gas and Unleaded Gasoline for several combinations of embedding dimensions and delay times. These outcomes clearly indicate that the high statistics shown in Table 3 are compatible with compounding GARCH effects. However, the results in Table 5 also indicate that conditional heteroskedasticity does not completely collect the nonlinearity contained in Natural Gas residuals and in Unleaded Gasoline residuals.

Table 5. BDS-G Tests Statistics for GARCH Residuals

		Embedding Dimension (*m*)				
		2	3	4	5	6
Natural Gas	**Time delay**					
	1	-1,44	-0,98	-0,57	-0,35	0,31
	2	0,45	0,22	0,15	0,59	1,37
	3	0,09	0,16	0,05	0,51	0,97
	4	-0,76	0,14	0,84	0,87	1,70
	5	2,59*	2,86*	3,06*	4,45*	5,18*
Unleaded Gas						
	1	-0,24	-1,02	-0,73	-0,43	0,16
	2	-0,19	-1,82	-1,56	-0,78	0,11
	3	0,92	0,68	1,17	1,51	1,85
	4	-0,05	1,08	1,82	2,72*	3,31*
	5	1,03	1,25	1,71	2,74*	2,78*
Crude						
	1	-1,07	-0,74	-0,28	-0,15	0,1
	2	0,74	0,54	0,91	1,06	1,01
	3	0,86	0,98	0,28	-0,09	1.88
	4	-0,04	-0,14	-0,23	-0,07	0,31
	5	1,59	0,89	0,63	1,03	1,01

Note: The critical values are 1.645, 1.960 and 2.575 for the 10%, 5% and 1% significance levels, respectively. * means rejection of the null hypothesis at the 1% level.

We turn now to confirm, with a different statistical procedure, whether future returns are compatible with a nonlinear explanation. To that end we analyze them with a direct test for linearity that has been shown to be as powerful as tests based on Grassberger-Procaccia's correlation integral (see Barnett *et al.*, 1997).

2.3 The Kaplan Test

The method described here is oriented towards situations where the functional form that generated the observed data is unknown, and the goal is to decide whether there is evidence of a deterministic mechanism. The main goal of Kaplan's test is to decide

whether the observed data $\{z_i\}_{i=1}^{T}$ are more consistent with a deterministic mechanism or with a stochastic model. In the case of a deterministic chaotic mechanism, a time series plot of the output of such process may be very difficult to distinguish visually from a stochastic process. In contrast, as is well known, the simple plot of z_i versus z_{i+1} often reveals the deterministic structure. In contrast, in the presence of stochastic data, this kind of plot will produce no structure, i.e., single-valuedness, rather than certain continuity.

The test proposed by Kaplan (1994) is based on the fact that for chaotic processes, unlike stochastic ones, if two points z_i and z_j are very close together, then their images are also close together. In consequence, the test is ultimately rooted on the evidence of the continuity of an underlying function, since if the hypothetical underlying function linking images and pre-images is continuous, then it is expected that points that are nearby are also nearby under their image. One way of applying Kaplan's statistic is to test for linearity against the alternative of nonlinear dynamics. To implement this procedure, one needs to compute the statistic from an adequately large number of linear stochastic processes that plausibly might have produced the data, and then compare the value of the test on such potential processes with the value of the test computed from the observed data.

More generally and formally stated, given a vector[8] $\mathbf{z}_t \equiv \left(z_t, z_{t-\tau}, z_{t-2\tau}, z_{t-3\tau}, ..., z_{t-(m-1)\tau}\right)$ embedded in *m*-dimensional phase space and obtained from the observed data set $\{z_i\}_{i=1}^{T}$, $\mathbf{z}_{t+\tau} = f(\mathbf{z}_t)$ will be called the *image* of the point $\mathbf{z}_t$ for a fixed positive integer time delay τ, say for example $\tau = 1$. For deterministic systems, nearby points in *m*-dimensional phase space will have nearby images. In contrast, for stochastic systems nearby points may have very different images. For a given embedding dimension *m* and for a given time delay τ, Kaplan's technique involves examining all pairs of points $\mathbf{z}_j$, $\mathbf{z}_k$ in terms of the distance between them $\delta_{j,k} = \left|\mathbf{z}_j - \mathbf{z}_k\right|$ and the distance between their images $\varepsilon_{j,k} = \left|\mathbf{z}_{j+\tau} - \mathbf{z}_{k+\tau}\right|$. Then one calculates averages of the values of $\varepsilon_{j,k}$ conditional on the corresponding value of $\delta_{j,k}$, that is:

[8] We have eliminated notational dependence on τ and *m* for clarity.

$$E(r) \equiv \overline{\varepsilon}_{j,k} \text{ for } j,k \text{ s.t. } \delta_{j,k} < r$$

In words, $E(r)$ computes the average distance of the images whose pre-images are *r*-close. For a deterministic system with continuous *f*, one expects that the average distance of the images will decrease as their corresponding pre-images are very close, in fact it will be expected that $\lim_{r\to 0} E(r) \to 0$. Note, however, that for stochastic systems this convergence is not likely because nearby pre-images may have very distinct images. Precisely, Kaplan's test statistic is:

$$K \equiv \lim_{r\to 0} E(r)$$

One way of interpreting the nonzero value of K is as the level of nondeterminism in the data. For stochastic systems K is expected to be higher than for near deterministic ones.

An appropriate null hypothesis (Ho) for many nonlinear dynamics tests is that the data arise from a linear dynamical system. In order to establish the significance of the test, one can generate many realizations of the Ho, and then estimate the significance empirically.

The null of "stochastic linear dynamical system" is not very specific. For instance, it does not describe simple quantities such as the mean and variance. One approach to make a specific Ho is to set the mean and variance to the same as that of the original data. In addition, and very importantly, the autocorrelation function and the histogram can be specified as being the same as that of the original data. We refer to surrogate data as random data generated with the same mean, variance, autocorrelation function and histogram as the original data.

In order to implement the analysis via surrogate data, one generates many realizations of the surrogate data, and calculates K independently on each one of them. To that end, one has to make sure that the embedding dimension *m* and time delay are the same for the surrogate data as for the original test data. If the measure of nondeterminism is smaller for the data than for the surrogate data, generated from a model that satisfies the null of stochastic linear dynamical system, then there is evidence that the null hypothesis should be rejected.

There are several measures that can be useful for providing a certain guarantee of coming to a conclusion about the null hypothesis. It is worthwhile to compute the

minimum value of K that is consistent with the surrogates. One possibility is to calculate directly the minimum value of K from the finite number of surrogates, and impute that value to the population of surrogates consistent with the procedure. Another, perhaps more attractive, option is to compute the mean and the standard error of the K values from the finite sample and then subtract a multiple (2 or 3) of the standard error from the mean in order to obtain an estimate of the population minimum. Finally, sometimes it is useful to compare the level of noise in the data versus the level of noise in the surrogate data sets, as K might be interpreted as the level of nondeterminism. To that end the ratio of the mean of the surrogates to the test data is computed. The output is interpreted as the number of times as much noise is in the surrogate as in the data.

2.4 Results with Kaplan Test

As stated before, the null hypothesis for Kaplan's test is stochastic linearity of the process. In fact, the test, as applied in this paper, can either accept or reject linearity. Kaplan's test statistics are displayed in Table 6 for embedding dimensions (*m*) 2, 3, 4 and 5. We have used twenty surrogates[9]; hence the mean, minimum, strength and standard deviations are over the surrogates. The test rejects[10] the null of linearity of the Natural Gas process at all dimensions. Similar results are found for Unleaded Gasoline and Crude futures returns, with the exception of dimension 3 for which the null is not rejected. In general, one might conclude that the null of linearity should be rejected in favour of non-linearity, which, as expected, is consistent with the result given by BDS-G statistics.

[9] Time delay has been fixed at 1 because, according to BDS-G results on Table 3, the null of IID is rejected regardless time delay, so we have used the most common time delay to facilitate future comparisons. However additional testing, not reported here, has been done for time delays distinct from 1, and similar results were obtained.

[10] We arrive at that conclusion by estimating the minimum K either as the minimum value of K from the finite number the surrogates or as the result of subtracting two times the standard deviation of the surrogates from the mean.

Table 6. Kaplan Tests Statistics in Energy Futures Returns under the null of stochastic linearity

	Embedding dimension	Mean K on surrogates	Std. Dev. of K on surrogates	Min K on surrogates	K Statistic on Returns	K strength
Natural Gas	2	0.04	0.003	0.04	0.013	3.0
	3	0.04	0.004	0.03	0.009	4.3
	4	0.04	0.009	0.02	0.010	3.9
	5	0.04	0.004	0.03	0.008	4.6
Unleaded Gas	2	0.023	0.002	0.020	0.016	1.2
	3	0.023	0.003	0.013	0.015	1.4
	4	0.022	0.004	0.010	0.015	1.5
	5	0.023	0.003	0.015	0.012	1.8
Crude	2	0.027	0.002	0.022	0.021	1.2
	3	0.027	0.003	0.019	0.020	1.3
	4	0.027	0.004	0.019	0.017	1.6
	5	0.029	0.005	0.022	0.012	2.3

Note: K is the Kaplan test statistic. Time delay is fixed at 1. Twenty surrogates were used to compute: Mean, Minimum, Standard Deviation and Strength. 'K strength' refers to the ratio Mean K / K statistic.

According to the results obtained in the preceding subsection, nonlinearity might be due to GARCH effects. We now turn to computing Kaplan's test under the null of GARCH (1, 1) structure. To this end, surrogates for each return are generated from a model that satisfies the corresponding GARCH parameters, which are described in Table 4. From a broad perspective, Kaplan's statistic (K) can be interpreted as a goodness of fit measure from fitting a continuous model of some fixed order to an infinite amount of data. Again, if this measure of fit is smaller for the data than for surrogate data, then there is evidence that the null hypothesis should be rejected. The results are displayed in Table 7. The evidence against GARCH effects is larger than that found with the BDS-G statistic (see Table 5). Now, the null is rejected at all embeddings for Natural Gas and Crude returns, while it cannot be rejected for the Unleaded Gasoline.

Table 7. Kaplan Tests in Energy Futures Returns under the Null GARCH (1,1) process

	Embedding dimension	Mean K on surrogates	Std. Dev. of K on surrogates	Min K on surrogates	K Statistic Returns	K strength
Natural Gas	2	0.044	0.004	0.032	0.013	3.3
	3	0.048	0.007	0.035	0.009	5.1
	4	0.045	0.006	0.031	0.010	4.4
	5	0.043	0.010	0.013	0.008	4.9
Unleaded Gas	2	0.018	0.002	0.013	0.016	1.2
	3	0.020	0.003	0.014	0.015	1.3
	4	0.020	0.004	0.009	0.015	1.3
	5	0.019	0.004	0.011	0.012	1.6
Crude	2	0.109	0.020	0.087	0.021	5.1
	3	0.111	0.018	0.068	0.020	5.4
	4	0.107	0.014	0.068	0.017	6.2
	5	0.111	0.024	0.081	0.012	8.8

Note: K is the Kaplan test statistic. Time delay is fixed at 1. Twenty surrogates were used to compute: Mean, Minimum, Standard Deviation and Strength. 'K strength' refers to the ratio Mean K / K statistic.

3. TEST FOR CHAOS

The main conclusion obtained from the preceding section is that nonlinearity in energy futures price movements cannot be rejected. It is not completely clear, according to Kaplan's test and BDS-G statistics, what exactly is the source of this nonlinear behaviour. In this section, we focus on testing whether the nonlinear dynamics found in the returns of the three energy futures has its origins in a chaotic skeleton. Through out this paper we consider chaotic in the sense of low-dimensional chaos, since high-dimensional chaos is confused with stochastic models[11]. To that end the notion of Lyapunov exponent is introduced since it is usually taken as an indication of the chaotic character of the underlying dynamical system. In the presence of noise, as happens with real-world data sets, the meaning of "detecting deterministic chaotic dynamics" is ambiguous. For this reason, when the presence of noise is small, Lyapunov exponents test for 'noisy chaos'. Moreover, under this circumstance, the estimated exponents can be interpreted as a measure of local stability. Following Fernández-Rodríguez *et al*. (2005), stability of the largest Lyapunov exponent is used to test for chaos.

3.1 The Largest Lyapunov Exponent

For a dynamical system, sensitivity to initial conditions can be quantified by the Lyapunov exponents. For example, consider two trajectories with infinitely close initial

[11] As Ruelle (1994) comments, noise can be always be interpreted as a deterministic time evolution in infinite dimension.

conditions on an attractor. For chaotic systems, points in a common neighbourhood in the phase space diverge with time, on average, at an exponential rate characterized by the largest Lyapunov exponent. This concept is also generalized for the *spectrum* of Lyapunov exponents, $\{\lambda_1, \lambda_2, ..., \lambda_n\}$, by considering a small *n*-dimensional sphere of initial conditions, where *n* is the number of equations (or, equivalently, the number of state variables) used to describe the system.

Lyapunov exponents offer information on how orbits on the attractor diverge (or contract) given the dynamic evolution of the system. The presence of a positive exponent is sufficient for diagnosing chaos and represents local instability in a particular direction. Note that for the existence of an attractor, the overall dynamics must be dissipative and the total rate of contraction must outweigh the total rate of expansion. Thus, even when there are several positive Lyapunov exponents, the sum across the entire spectrum is negative.

Experimental data often consist of time series from a single observable, and then the method of delays is generally employed as a proper technique for attractor reconstruction. Given the conditions provided by the ergodic theorem of Oseledec (1968), one can expect that two randomly chosen initial conditions will diverge exponentially at a rate given by the largest Lyapunov exponent ($\lambda_{\max}$).

The different methods for computing Lyapunov exponents from time series that have been proposed so far can be divided into two classes: (i) direct methods like Wolf *et al*. (1985) or Rosenstein *et al*. (1993), which assume that the initial divergence between initial states grows at the exponential rate given by $\lambda_{\max}$ in the reconstructed state space of a time series; and (ii) Jacobian methods like McCaffrey *et al*. (1992), Nychka *et al*. (1992) or Shintani and Linton (2004), where data are used to estimate (using non-parametric techniques as kernels and neural nets) the Jacobians from an estimation of the conditional expectation of the process. This finally allows $\lambda_{\max}$ to be estimated.

In this regard, one important disadvantage of Jacobian methods is that in the presence of observational noise, the noise is amplified by higher order nonlinearities[12]. Besides, tangent methods need, a priori, to fix a neural network structure. We refer the reader to Schreiber and Kantz (1995) for a detailed discussion. In this paper we have

[12] Similarly, if the dimensionality of the underlying system increases, the evaluation of the diagonalized Jacobian requires extensive multiplication of the individual matrix elements of the Jacobian.

opted for direct methods, and then we make use of a simple direct method for estimating the largest Lyapunov exponent $\lambda_{\max}$ of a time series. This technique was proposed by Rosenstein *et al*. (1993).

3.2. Testing for stability of the Largest Lyapunov Exponent

Unfortunately, in practical implementations with finite time series, it is possible that Rosenstein's algorithm finds positive values for the Lyapunov exponent, for any pure random process. This problem is relevant in energy returns since nonlinear stochastic models, like GARCH processes, are alternative models to the chaotic behaviour.

In order to circumvent this problem, Fernández-Rodríguez *et al*. (2005) have shown that, for a large enough sample size, Lyapunov exponents will converge to some stable values directly associated with the complexity of the attractor. However, nothing guarantees the stability of the Lyapunov exponent if the process is non-chaotic stochastic. For GARCH processes, as the number of observations increases, the variability of the largest Lyapunov exponent will increase continuously.

Based on the stability of the largest Lyapunov exponent, Fernández-Rodríguez *et al*. (2005) have proposed a test that has 'low-dimensional chaos' as the null hypothesis, while the alternative is that of a stochastic process. The test has great power against a rich variety of stochastic processes (either linear or nonlinear). In contrast to other statistical procedures, the test detects GARCH process even for small data sets.

Given the observed time series $\{z_i\}_{i=1}^{T}$, the new statistical procedure takes the following steps:

1. Divide $\{z_i\}_{i=1}^{T}$ into different subsamples, each of which contains the precedent: $\{z_1, z_2, ..., z_{N_i}\}$ $\quad i = 1:r$.
2. Obtain the empirical distribution of the largest Lyapunov exponent from 100 moving block bootstraps for the subsamples obtained in step 1. The largest exponent is calculated according to Rosenstein *et al*.'s methodology.

3. Estimate the dominant Lyapunov exponent by computing the mean of the distribution of the 100 largest Lyapunov exponents computed from each sample size, N_i: $\left\langle \hat{\lambda}_{\max}\left(N_i\right)\right\rangle$

4. Test for linear dependence between $\left\langle \hat{\lambda}_{\max}\left(N_i\right)\right\rangle$ and the sample size N_i, $i=1,...,r$. To that end, the following regression is calculated:

$$\left\langle \lambda_{\max}(N_i)\right\rangle = \alpha_0 + \alpha_1 N_i + \varepsilon_i \quad \text{for } i = N_1, N_2, ..., N_r = T$$

5. Use the estimated parameter $\hat{\alpha}_1$ to test if the largest Lyapunov exponent does not increase with sample size[13], indicating an underlying deterministic process:

$$H_0 : \alpha_1 \leq 0 \text{ (chaotic process)}$$
$$H_A : \alpha_1 > 0 \text{ (stochastic process)}$$

Due to the fact that this procedure for testing the stability of the largest Lyapunov exponent relies on Rosenstein *et al.*'s algorithm, there exist two parameters that need to be selected. Firstly, the embedding dimension has been selected between 2 and 6, and time delay has been fixed at 1 for all embeddings. These reconstruction parameters are habitual in the financial literature. However, as stated above, selecting appropriate parameters is important for any successful subsequent analysis on the reconstructed phase space. Precisely, the estimation of the largest Lyapunov exponent is based on the reconstructed space. Moreover, according to the output obtained in Table 5, the time delay parameter seems to be crucial. In consequence, given the importance of a correct selection, we have also looked for optimal reconstruction parameters. Several algorithms have been suggested to find 'optimal' values for *m* and τ (see Soofi and Cao 2002, for a complete summary).

To find the optimal τ, an important class of algorithms directly considers the geometry of the reconstructed attractor. In this paper we use one of the most popular approaches that consists in finding the first minimum of mutual information of the reconstructed states (Fraser and Swinney, 1986). Once time delay has been chosen, the embedding

[13] Critical values are given in Table I of Fernández-Rodríguez *et al*. (2005).

dimension can be determined. Most of the methods for determining *m* are based on continuity tests for the induced flow in the reconstructed space or for the embedding itself. The method known by average false nearest neighbours (Cao, 1997) is used in this paper.

3.3 Results

We now apply Fernández-Rodríguez *et al*.'s test to the standardized residuals. The results are presented in Table 8. Evidence of chaotic behaviour is found for the returns of Natural Gas and Unleaded Gasoline, when the embedding dimension is 2 and time delay is 1. For the remaining cases, the null of a chaotic process is rejected at the 1% level. Interestingly, in accordance with the last row of Table 8, the three energy returns are compatible with a chaotic skeleton when reconstruction is carried out at the optimally selected parameters. Particularly, our conclusion about Natural Gas returns contrast sharply with that achieved by Chwee (1998). This difference can be explained partly because our test is different (we test for the null of chaos via stability of the Lyapunov exponent); partly because reconstruction is carried out according to optimally selected parameters[14]; and partly due to the fact that we are using a different sample period. Given these results, the next section will deal with modelling the underlying dynamics. In order to accomplish that, the 'optimal' reconstruction parameters will be taken into account. Forecast comparisons between chaotic equations and well known stochastic models are also performed.

[14] The crucial role played by 'time delay' parameter is now evident. Note that Chwee's results and those presented throughout this paper coincide for time delay fixed at 1 and embedding dimensions 3, 4, 5 and 6.

Table 8. Tests for the Stability of the largest Lyapunov exponents

Embedding Dimension Time Delay = 1	Natural Gas	Unleaded Gas	Crude
2	2.34e-4 (5.06)	-2.12e-6 (-0.11)	2.11e-3* (6.63)
3	1.49e-4* (6.01)	6.85e-5* (4.17)	2.10e-4* (6.76)
4	9.79e-5* (6.30)	7.39e-5* (5.05)	1.21e-4* (6.83)
5	8.28e-5* (6.61)	7.67e-5* (5.17)	8.61e-5* (7.08)
6	6.15e-5* (7.71)	6.20e-5* (4.18)	6.36* (5.70)
Optimal Parameters [dimension, time delay]	-4.92e-5 (-10.01) [5,5]	-2.98e-5 (-9.24) [5,5]	-5.98 (-12.93) [6,5]

Notes: The sample periods are April 3, 1990 through October 19, 2005 (Natural Gas and Crude) and March 3, 1992 through January 31, 2006 (Unleaded Gas). OLS estimation of the linear regression $\langle \lambda_{\max}(T) \rangle = \alpha_0 + \alpha_1 T + \varepsilon_t$ with *t*-ratio in parentheses. *Denotes rejection of the null hypothesis Ho: $\alpha_1 \leq 0$ (deterministic process) at the 1% level, following critical values of Fenández-Rodríguez *et al*. (2005). Optimal reconstruction parameters have been chosen according to the 'minimum of the mutual information function', Fraser and Swinney (1986); and the 'average false nearest neighbours' Cao (1997).

4. DYNAMIC MODELLING WITH GENETIC ALGORITHMS

In general, the interest in searching for predictable components in energy futures is well known (see, Moshiri and Forouzan 2006, Sertelis and Gogas 1999, Chwee 1998 and Fama 1991). So far we have shown that the three energy futures returns studied in this paper are compatible with a nonlinear chaotic explanation. Once that space state reconstruction can be done in a presumably optimal way, the following step consists in estimating an underlying dynamic for each return. Artificial neural networks (see, Soofi and Cao 2002) and recently genetic algorithms (see, Beenstock and Szpiro 2002 and Alvarez *et al*. 2001) have dealt with this issue. In this last section, we use genetic algorithms to model the nonlinear dynamics found in energy returns. In addition, a comparative study with a GARCH (1,1) model and a naïve one is carried out.

The tenet of a genetic algorithm is that uses the concepts of evolutionary development to breed equations whose performance improves with each generation. A genetic algorithm is likely to provide a deeper understanding of the dynamics of a

generating process, since the functional solution is provided in analytical form. The estimation of time series models has also been studied by genetic algorithms (see, Koza 1992, Szpiro 1997, Álvarez *et al*. 2003). One of the attributes that makes them interesting is that gradient type algorithms (think of artificial networks, among others) search from one single point to the next; meanwhile genetic algorithms through principles of selection, crossover and random mutation, tend to select superior dynasties, and therefore can be considered global, rather than local, searchers. Finally, one of the advantages of these algorithms is that they are robust approaches to determining the functional form in nonlinear time analysis (Szpiro 1997). Certainly, this is an interesting property in the context of the present paper.

Takens' theorem guarantees that the system's state information can be recovered from a sufficiently long observation of the output time series. According to the theorem, it also follows the existence of a smooth map $E : R^m \rightarrow R$ satisfying:

$$z_t = E\left(z_{t+\tau}, ..., z_{(t+m\tau)}\right)$$

The first step is to use past information to reconstruct the dynamics. Note that this step has already been considered when we introduced the method of the delay coordinates in previous sections. The next step is to build the model $E(\cdot)$. Various techniques can be considered to accomplish the task of approximating the function $E(\cdot)$. Examples of these techniques are methods based on polynomial fitting, neural networks and radial basis functions (Soofi and Cao, 2002). More recently, a genetic algorithm search procedure based on Darwinian theories of natural selection and survival has been described (Álvarez *et al*., 2001; Koza, 1992).

The genetic algorithm, hence, is developed to approximate the equation (in symbolic form) that describes a given time series. The symbols conform an alphabet that can be interpreted through a simple grammar: two characters from the alphabet are combined by an arithmetic operator enclosing this expression in parentheses. The genetic algorithm is a stochastic search algorithm which acts on a population of possible solutions (Mitchell, 1996). The basic idea is to encoded potential solutions as 'genes', then new solutions can be produced by `mutating' members of the current population, and by 'mating' two solutions together to form a new solution. The better solutions are selected to breed and mutate, and the worst ones are discarded. The evolutionary steps

are repeated until a number of generations (a priori determined by the researcher) is achieved. Therefore, given a time series $\{z_t\}_{t=1}^{T}$, a set of candidate equations of the form $E(\cdot)=\big((A\otimes B)\otimes(C\otimes D)\big)$, where *A*, *B*, *C* and *D* are lagged values of z_t or real number constants, and where $\otimes$ stands for the arithmetic operators (+,-,×,÷), is randomly generated. It has been proved that these four operators do describe complex time behaviours (see Szpiro, 1997; Yadavalli, 1999). Each individual $E(\cdot)$ is used to compute estimates of all z_t in part of the time series (the training set). In order to compute the fitness of each equation-string a criterion that measures how well the equation explains the variance of the training set is defined by:

$$R^2 = 1 - \frac{\sum_{t=m+1}^{T}\left[z_t - E(\cdot)\right]^2}{\sigma}$$

where σ represents the variance of the training data set. The closer to the unit value R^2, the better will be the prediction based on $E(\cdot)$, while low values indicate a poor forecast capability of the algorithm. Equation strings are ranked in descending order of their fitness, and then mates are selected according to their R^2 in order to exchange parts of the character strings between the two 'parents', therefore equations (genes) less fitted to the data are discarded. As a result of this crossover, new complicated offspring are generated. Since the length of the strings might turn out to be a real burden, an upper bound is fixed. Finally, some mutations are applied to strings, despite the fact that best solutions are protected from mutation. The evolutionary process is repeated a large number of times. In the end, a complex analytical form $\hat{E}(\cdot)$ is obtained. To summarize, this procedure is an evolutionary algorithm that attempts to approximate the functional form underlying the data. This provides more direct knowledge of functional relations between past, present and future values of the time series.

In order to implement the genetic algorithm, the first step is to select the parameters upon which the dynamics will be reconstructed. Our selection has been conducted following the techniques described in subsection 3.2, and reported in the last row of Table 8. In addition the researcher also has to select a training set. In this regard, for each data set we have decided on the first 3800 observations for the natural gas and crude data sets, and on the first 3400 observations for the unleaded gas data set, leaving the last 92 data points to make predictions. The scalar estimated functions for the three

energy returns are given in Table 9[15], together with some statistics. The Q2(15) statistics show that for the three data sets no ARCH effects are present in the residuals.

Table 9. Genetic Algorithms: In-Sample Equations and Diagnostics

Future Returns	Estimated Equations with GA	K-S	Q2(15)
NATURAL GAS	$\hat{E}^{NG} = \left(z_{t-20} - z_{t-5}\right) \cdot \left(\frac{z_{t-10} - z_{t-20}}{8.73 \cdot z_{t-5}} - z^2{}_{t-5} \right)$	0.46 (0.00)	9.41 (0.22)
UNLEAD GASOLINE	$\hat{E}^{U.GAS.} = z_{t-10}\left(z_{t-5} + z_{t-20}\left(1 - 85.94 z_{t-5}\right)\right)$	0.49 (0.00)	8.08 (0.62)
CRUDE	$\hat{E}^{CRUDE} = z_{t-5}\left(2z_{t-10} - z_{t-30} + \frac{z^3{}_{t-25}}{z_{t-10}}\right)$	0.47 (0.00)	6.53 (0.96)

Notes: The in-sample periods are April 3, 1990 through May 31, 2005 for Natural Gas and Crude returns, and March 3, 1992 through September 8, 2005 for Unleaded Gas returns. The Q2(15) statistic is the Ljung-Box test on the squared residuals. The Kolmogorov-Smirnof statistic tests for standard normal distribution on the residuals (p-values in parenthesis).

We turn now to the performance of the estimated equations applied to the problem of forecasting. The null of chaos driving energy futures returns has not been rejected by our findings. However, it is insightful to compare the GA forecast's performance with other potential sources of nonlinearity. To that end the GA predictor is compared with two alternative market representations, namely, a naïve predictor $z^{naive}{}_{t+1} = z_t$ and a GARCH (1, 1) predictor. Table 10 presents the in-sample parameter estimates together with some diagnostics. Note that the estimates are positive and significant.

[15] In order to estimate the three GA equations, the following parameters regarding the evolutionary process have been used: Number of individuals in the population: 120. Total number of arguments and operators allowed: 16. Number of arguments and operators for the initial individuals: 7. Number of generations that determines the stopping criteria: 1000. Probability of mutation has been fixed at 10%.

Table 10. GARCH(1,1) In-Sample Estimates and Diagnostics

Coefficients	Natural Gas	Unleaded Gas	Crude
W_0	1.1e-4 (3.49)	7.14e-5 (2.03)	2.03e-4 (2,76)
ARCH(1)	0.25 (5.15)	0.34 (4.81)	0.07 (5.68)
GARCH(1)	0.69 (15.32)	0.57 (52.15)	0.93 (92.70)
Diagnostics			
Kolmogorov-Smirnof	0.05 (0.00)	0.46 (0.00)	0.04 (0.00)
Q2(15)	10.83 (0.76)	7.61 (0.93)	21.51 (0.12)

Notes: The in-sample periods are April 3, 1990 through July 7, 2005 for Natural Gas and Crude returns, and March 3, 1992 through September 8, 2005 for Unleaded Gas returns. The Bollerslev-Wooldrige robust standard errors are reported in the parentheses. The Kolmogorov-Smirnof statistic tests for standard normal distribution on the standardized residuals (p-values in parenthesis). The Q2(15) statistic is the Ljung-Box test on the squared standardized residuals (*p*-values in parenthesis).

Forecasts are computed for the last 92 returns of each market. To that end, we use two statistical loss functions:

$$MSE = n^{-1}\sum_{t=1}^{n}\left(z_t - \hat{z}_t\right)^2$$

$$MAD = n^{-1}\sum_{t=1}^{n}\left|z_t - \hat{z}_t\right|^2$$

The MSE loss function is a typical mean squared error metric, while the MAD loss function is generally more robust to the possible presence of outliers than the MSE criterion.

To compare among the three models (GARCH, naïve and GA) we make use of the Diebold and Mariano (1995) test of no difference in the accuracy of two competing forecasts. Assuming that the parameters of the system are set a priori and do not require estimation, the Diebold-Mariano test statistic is designed as follows: let $\left\{\hat{z}_{i,t}\right\}_{t=1}^{n}$ and $\left\{\hat{z}_{j,t}\right\}_{t=1}^{n}$ denote two sequences of forecasts of the series $\left\{z_t\right\}_{t=1}^{n}$ generated by two competing models *i* and *j* and let $\left\{e_{i,t}\right\}_{t=1}^{n}$ and $\left\{e_{j,t}\right\}_{t=1}^{n}$ be the corresponding forecast errors. Given a loss function $g(\cdot)$ (in this case MSE or MAD), we can define the loss differential between the two competing forecasts (where *i* stands for the benchmark model, GA, and *j* for one of the other competing models) as $d_t \equiv [g(e_{i,t}) - g(e_{j,t})]$.

Diebold and Mariano (1995) showed that the asymptotic distribution of the sample mean loss differential $\bar{d} = n^{-1}\sum_{t=1}^{n} d_t$ is $\sqrt{n}\left(\bar{d} - \mu\right) \xrightarrow{d} N\left(0, V(\bar{d})\right)$. Under the null of equal forecast accuracy the statistic[16] $\bar{d} \Big/ \sqrt{\hat{V}(\bar{d})} \sim N(0,1)$.

Table 11. Diebold-Mariano Tests Out-Sample Period

Future Returns	GA against GARCH		GA against Naïve	
	MSE	MAD	MSE	MAD
Natural Gas	-4.78 (0.00)	-4.53 (0.00)	-3.20 (0.00)	-4.85 (0.00)
Unleaded Gas.	-6.31 (0.00)	-4.09 (0.00)	-3.42 (0.00)	-6.57 (0.00)
Crude	-3.57 (0.00)	-3.38 (0.00)	-3.42 (0.00)	-3.95 (0.00)

Notes: The out-sample periods are June 1, 2005 through October 7, 2005 (for Natural Gas and Crude returns); September 9, 2005 through January, 31 2006 for Unleaded Gas returns. Diebold-Mariano statistics test for equal forecast accuracy, *p*-values are reported in parenthesis.

Table 11 reports the Diebold-Mariano test when the benchmark is the GA model, compared to each one of the other models. It is evident that the GA predictor significantly outperforms the GARCH and the naïve models at any usual confidence level. Remarkably, the sign of the Diebold-Mariano statistic, when the GA model is compared to the GARCH model and to the naïve one, is always negative, implying that the GA's loss is lower than that implied by these two models.

It is important to note that, from our results in terms of forecasting, it cannot be concluded that estimation procedures based on GA are superior to other well-established statistical techniques. Readers interested on this kind of competition are suggested to see Neely and Weller (2001). In this regard, observe that, providing that the null of chaos has not been rejected, there is no reason to expect that heteroskedastic models or random walk models forecast better than others. Even in the case of chaos, a GARCH model will presumably forecast conditional variance very accurately.

[16] An estimate of the asymptotic variance is $\hat{V}\left(\bar{d}\right) = n^{-1}\left(\hat{\gamma}_0 + 2\sum_{k=1}^{h-1} w_k \hat{\gamma}_k\right)$, where $\hat{\gamma}_k = n^{-1}\sum_{t=k+1}^{n}(d_t - \bar{d})(d_{t-k} - \bar{d})$, and where h is the step-ahead-forecast.

Another interesting observation is that the method of estimation shown in this study is univariate, so it will be desirable to complete the study with a multivariate time series approach. In this regard, the embedding dimension can guide the selection of the number of relevant variables to include in the multivariate model. We leave these aspects as open questions for further research.

5. CONCLUSION

This paper examines and, if possible, estimates the nonlinear and chaotic nature of three energy futures, namely: natural gas, unleaded gasoline and light crude oil. Nonlinearity has been studied using the generalized BDS statistic, together with Kaplan's test. The results show that nonlinearity cannot be rejected. According to our findings, the source of nonlinearity is not clearly due to conditional heterokedastic variance. The recently generalized BDS test has shown that if the data are analyzed with appropriate delay times, nonlinearities are better detected. As a result, energy futures' returns are compatible with a general form of nonlinearity. In order to further investigate a potential explanation for this nonlinearity the null of chaos has been tested.

In order to test for chaos, the stability of the largest Lyapunov exponents have been studied. We have found evidence of nonlinear chaotic dynamics in all three energy futures' returns. This is not the first time that evidence in favour, and against, of chaos has been detected in energy prices (see Serletis and Gogas, 1999 and Chwee, 1998, respectively). A natural question arises: Does evidence of chaos depend on the test procedure used by the researcher? This question is left for future research.

The next step has been to estimate the potential motion equation for each process. This has been done via genetic algorithms, and the deterministic equations that best fit data have been supplied. Furthermore, we have used these estimated equations to forecast short term movements in futures' prices. The results show that, although forecast errors are smaller than those computed with well-established stochastic models, further research needs to be done. In this regard, a multivariate approach using genetic programming should be further investigated.

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