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Nonlinearity and intraday efficiency tests on energy futures markets[☆]

Tao Wang [a], Jian Yang [b,*]

[a] Department of Economics, Queens College and the Graduate Center, The City University of New York, Flushing, NY 11367, United States
[b] The Business School, PO Box 173364, University of Colorado Denver, Denver, CO 80217-3364, United States

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ABSTRACT

Using high frequency data, this paper first time comprehensively examines the *intraday* efficiency of four major energy (crude oil, heating oil, gasoline, natural gas) futures markets. In contrast to earlier studies which focus on in-sample evidence and assume linearity, the paper employs various nonlinear models and several model evaluation criteria to examine market efficiency in an out-of-sample forecasting context. Overall, there is evidence for intraday market inefficiency of two of the four energy future markets (heating oil and natural gas), which exists particularly during the bull market condition but not during the bear market condition. The evidence is also robust against the data-snooping bias and the model overfitting problem, and its economic significance can be very substantial.

1. Introduction

For most of its scientific life, the field of finance has debated the question of market efficiency (Chordia et al., 2005). The weak-form market efficiency suggests that the security prices traded in a (weak-form) efficient market follow a random walk (or more precisely a martingale) and cannot be predicted based on historical price information.[1] Hence, randomness or unpredictability of asset returns can generally be claimed to closely relate to market efficiency. The inference on market efficiency carries important implications to practitioners, for example, to portfolio managers for the design of trading strategies, and to financial managers for the equity financing decision.

Numerous earlier works have been conducted to examine weak-form market efficiency in the context of asset return predictability based on past returns. In particular, these works typically use the autocorrelation test and/or the variance ratio test of Lo and MacKinlay (1988). The works using the autocorrelation test include Lee et al. (2000), Chordia et al. (2005) on stock markets and Liu and He (1991) and Liu (2007) on currency markets, while the works using the variance ratio test include Lee et al. (2000), Chaudhuri and Wu (2003), Patro and Wu (2004) and Bianco and Renò (2006) on stock markets, and Liu and He (1991) and Pan et al. (1997) on currency markets.

Noteworthy, however, both the autocorrelation test and the variance ratio test assume linearity and only investigate serial uncorrelatedness rather than martingale difference, which was already pointed out in Hsieh (1991) and McQueen and Thorley (1991) and more recently reemphasized by Hong and Lee (2003). Theoretically, as discussed in McQueen and Thorley (1991), existence of fads or rational speculative bubbles suggests the possibility of nonlinear patterns in asset returns. Or, if the world is governed by a not-too-complex chaotic process, it should have short-term nonlinear predictability (in mean) but not linear predictability (Hsieh, 1991, p.1845). Empirically, a nonlinear time series can have zero autocorrelation but a non-zero mean conditional on its past history (Hong and Lee, 2003). Hence, both the autocorrelation test and the variance ratio test may fail to capture predicable nonlinearities in mean and could yield misleading conclusions in favor of the random walk (martingale) hypothesis.

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* Corresponding author. Tel.: +1 303 556 5852; fax: +1 303 556 5899.
E-mail addresses: tao.wang@qc.cuny.edu (T. Wang), jian.yang@ucdenver.edu (J. Yang).

[1] The terms "random walk" and "martingale" have been interchangeably used in the efficient capital markets literature. However, it is the martingale property (or unpredictability) of security prices that is of essential interest to this huge body of the literature (Fama, 1991). Strictly speaking, the innovations series is independent and identically distributed for "random walk", while it is a martingale difference sequence for "martingale."

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This study examines intraday market efficiency and return predictability on major energy futures markets. We seek to contribute to the literature in the following important aspects. First, although few earlier studies explore intraday volatility behaviors of electricity futures markets (e.g., Higgs and Worthington, 2005) or use nonlinear models to investigate daily oil futures market efficiency and return predictability (Fujihara and Mougoué, 1997; Moshiri and Foroutan, 2006; Matilla-Garcia, 2007; Shambora and Rossiter, 2007), our study is the first to investigate *intraday* return predictability on major energy futures markets (crude oil, heating oil, gasoline, natural gas). It is surprising to note that despite intraday transactions are nowadays common and surveys of market participants indicate that technical analysis is placed with more emphasis the shorter the time horizon, the study of predictability based on past returns with high frequency data is still very limited (Bianco and Renò, 2006; Marshall et al., 2008). Also, even casual observations can clearly reveal that intraday price behavior can be vastly different from daily price behavior, as a large swing within the day can end up with little change in the end-of-day closing price. To this end, our study on intraday price behavior (especially in the context of exploiting potential nonlinearity-in-mean) fills an important gap on energy markets in particular and (to a large extent) financial markets in general.[2]

Second, we extend the literature by applying a number of nonlinear models that allow for both potential nonlinearity-in-mean and nonlinearity-in-variance. In particular, some variants of the popular nonlinear models used in many previous studies are used in this study.[3] While the studies cited above using the autocorrelation test and/or the variance ratio test only focus on in-sample evidence and typically fail to allow for potential nonlinearity-in-mean, recent studies on energy markets (Moshiri and Foroutan, 2006; Matilla-Garcia, 2007; Shambora and Rossiter, 2007; Agnolucci, 2009) have focused on nonlinear models and out-of-sample performance, which also mitigates the concern of in-sample overfitting for nonlinear models. This study further extends these recent studies by using the recent White's Reality Check test (Sullivan et al., 1999) to address the concern of data-snooping bias (i.e., spuriously superior predicative ability of some complex models due to chance).[4] When several forecast models using the same data are compared, it is crucial to take into account the dependence among these models, which otherwise may result in misleading inference due to data-snooping bias.[5]

Finally, similar to Swanson and White (1997), Gencay (1998, 1999), Hong and Lee (2003) and Yang et al. (2008), this study presents evidence based on both statistical and economic criteria. Few earlier random walk behavior studies on futures markets have considered economic criteria as measured by magnitude of trading returns and particularly the direction of forecasted price changes, which have practical value to investors and other decision-makers. For example, Moshiri and Foroutan (2006) and Matilla-Garcia (2007) focus on statistical criteria, while only Shambora and Rossiter (2007) have explored the importance of trading rule profitability (as an economic criterion) to evaluate the forecasting performance on energy futures markets. Moreover, the direction of changes as an alternative economic criterion has been little explored on futures markets. From a perspective of decision-making under uncertainty, there exist important circumstances under which this criterion is exactly the right one for maximizing the economic welfare of the forecaster (Leitch and Tanner, 1991; Hong and Lee, 2003). Directional predictability in asset returns also has important implications for market timing and the resulting active asset allocation management. Hence, we are perhaps the first to comprehensively report evidence on both (out-of-sample) trading rule profitability (particularly based on multiple nonlinear models) and the predictability of direction of changes for major energy futures markets. The rest of this paper is organized as follows: Section 2 presents econometric methodology; Section 3 describes the data; and discusses the empirical results; and finally, Section 4 concludes the paper.

2. Econometric methodology

To forecast intraday energy futures returns (Y_t) using their past returns, we use various popular nonlinear models to estimate and predict $E(Y_t|I_{t-1})$, where $I_{t-1}=\{Y_{t-1},Y_{t-2},\ldots,Y_{t-d}\}$ is the information set available at time $t-1$ (where $d=1$ in this study). These models explore the possibility that intraday energy futures returns are not a martingale, and have the conditional mean dependence in a complicated form (i.e., nonlinearity-in-mean), and/or the dependence in higher (e.g., second) moments (i.e., nonlinearity-in-variance). We certainly do not assume that the limited number of the nonlinear models can capture all potential nonlinearities. However, they do represent many of the most popular nonlinear models widely-used in the literature thus far.

With the martingale model $Y_t=\mu+\varepsilon_t$ as the benchmark for comparison with other models, we consider the following popular linear and nonlinear models: the autoregressive model (AR(d)), generalized autoregressive conditional heteroskedasticity model (GARCH(p,q)), feedforward artificial neural network (NN(d,q)), functional coefficient model (FC(d,L)), nonparametric regression model (NP (k,m)), and some combinations of these models. The estimation of the AR(d) and GARCH(p,q) models is relatively standard, using the ordinary least squares method and the maximum likelihood method, respectively. Below we briefly discuss how to implement more complicated nonlinear models used in this study (i.e., neural network, functional coefficient and nonparametric regression models).

2.1. The artificial neural network model

Artificial neural networks have been popular in capturing potential nonlinearity-in-mean in economic time series. A major advantage of neural networks over other commonly-used nonlinear time series models is that a class of multilayer neural networks can well approximate a large class of functions. The basic structure of neural networks combines many 'basic' nonlinear functions via a multilayer structure. Typically, there is one intermediate, or hidden, layer between the inputs and output. The explanatory variables simultaneously activate the units in the intermediate layer through some function Ψ and the output is subsequently produced through some function Φ from the units in the intermediate layer, which can be summarized by the following equations:

$$h_{i,t} = \Psi(\gamma_{i0} + \sum_{j=1}^{m}\gamma_{ij}X_{j,t}) \qquad i = 1,\ldots,q \tag{1}$$

[2] To our knowledge, Hong et al. (2007) is the only noticeable exception, which comprehensively use a variety of nonlinear models to exploit intraday predictability of several currency futures markets.

[3] Like many earlier studies, a caveat here is that the inference should still be interpreted in light of the limited number of models we examine in this study. In general, martingale means the existence of neither linear nor nonlinear dependence, and we have to test all possible nonlinear dependence to rule out the martingale property of energy futures returns, which is practically impossible. For example, some recent studies (e.g., Fan et al., 2008; Ghaffari and Zare, 2009) also employ the genetic algorithm and adaptive neuro fuzzy inference systems to forecast energy prices, which are not considered here.

[4] As discussed in Campbell et al. (1997, p. 523–524), the problems of overfitting and data-snooping are related but distinctively different. A typical symptom of overfitting is an excellent in-sample fit but poor out-of-sample performance, while data-snooping refers to excellent but spurious out-of-sample performance. The Reality Check test is not yet commonly used in financial research, with only a few exceptions (e.g., Qi and Wu, 2006).

[5] By using multiple models and focusing on out-of-sample performance, we essentially take the model selection approach of Swanson and White (1997), rather than the more traditional hypothesis testing approach as taken in either the autocorrelation test or the variance ratio test. As discussed in Swanson and White (1997), unlike the traditional hypothesis testing approach, the model selection approach does not require the specification of a correct model for its valid application. By contrast, earlier empirical findings based on variance ratio tests are quite sensitive to potential model misspecification.