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Do wheat futures returns exhibit long-range dependence?

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Abstract

The efficient market hypothesis, where asset prices follow a random walk and incorporate all relevant information, is often invoked in financial economics. There is some evidence however to suggest that some asset prices do not follow random walks but display long-range dependence. Such systematic behavior of past returns is of interest to traders. This article examines long-range dependence in wheat futures prices using rescaled range analysis and the Hurst exponent. Since this estimate is biased when long-range dependence is absent and its distribution is unknown, a Monte Carlo simulation approach is proposed. Results show that wheat futures prices show no evidence of long-range dependence and there are no profitable trading rules.

JEL classifications: C22, Q13

Keywords: Wheat futures; Long-range dependence; Hurst exponent

1. Introduction

Over the last 40 years, there has been a burgeoning empirical literature on asset pricing behavior, and much of modern financial economics is based on the efficient market hypothesis where all public information is discounted. Asset prices only change therefore when new information becomes available and today's price change is caused only by today's unexpected news. There is some evidence to suggest however that asset prices exhibit persistent behavior over long time periods. Such correlation at long lags is termed long-range dependence, long memory, or persistence, and there are distinct but nonperiodic cyclical patterns, which are predictable. More specifically, long memory is present when the observations are not independent, that is, where an observation is affected by previous observations. This finding has important pricing implications for financial economics. For example, martingale processes are inconsistent with long-term memory, and traditional tests of the capital asset pricing model and the arbitrage pricing theory are invalid because usual statistical inference is inappropriate (Lo, 1991).

The efficient market hypothesis is where a random walk, or more strictly a martingale (Samuelson, 1965), characterizes price behavior, which has no memory, and where returns are white noise. This investment theory implies that it is impossible to make long-run profits by predicting trends. As Peters (1991, p. 13) observes, "An efficient market cannot be gamed because not only do the prices reflect known information, but the large number of investors will ensure that the prices are fair." The success of traders however depends on their ability to forecast future asset price movements, particularly in the long run.[1] To test long-range dependence in asset returns, rescaled range analysis and its key parameter, the Hurst exponent, is often used.

The analysis of long-range dependence is beneficial to traders in identifying those assets that have greater predictability. For example, Rogers (1997) shows that the existence of long-range dependence allows for profitable arbitrage opportunities without any risk. A trader would trade only in assets, which look promising in any given time period: if the gain in investment is too high or too low, the asset is immediately sold and the trader waits until the end of the period thereby ensuring bounded gains. As a second example, portfolios of assets could be created with given Hurst exponents and profit-generating characteristics, and if an asset falls below a threshold, investment positions could be closed.

Initial studies of nonperiodic, long-range dependence date from Hurst (1951, 1957) in the field of hydrology. In economics,

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[1] Typically, traders do not react to new information immediately, but wait for other confirming information. Where they react unevenly once a trend is established, asset prices follow a biased random walk.

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trade and business cycles often exhibit long-range dependence, and following Mandelbrot (1971) attention has turned to its presence in financial asset returns where the evidence is mixed. For example, Greene and Fielitz (1977) find its presence in the returns of many securities on the New York Stock Exchange, while Karytinos et al. (1999) for exchange rates and Sadique and Silvapulle (2001) for stock prices find long-range dependence in only half of cases studied.

The literature on long-range dependence in agricultural futures prices using the Hurst exponent is small and relates to North American contracts. Again the evidence is mixed. For U.S. contracts, Helms et al. (1984) find long-range dependence for returns to soybean products, as does Corazza et al. (1997) for corn, oats, soybeans, soybean meal, and soybean oil. Jin and Frechette (2004a) find widespread evidence of long-range dependence in U.S. futures returns in 13 of 14 agricultural commodities studies, including wheat, and Sephton (2009), with the same dataset, generally affirms these results. By contrast, Barkoulas et al. (1999) find strong long-range dependence in U.S. futures returns to corn, soybean meal, sugar, and wheat; weaker evidence in returns to cotton, coffee, and soybean oil; and none in returns to six other agricultural commodities. Similarly, Elder and Jin (2009) find long-range dependence in around half of 14 U.S. agricultural commodity futures returns studied. More conflicting evidence is found by Wei and Leuthold (2000): for U.S. futures returns to corn, soybeans, wheat, hogs, coffee, and sugar, Hurst exponents show long-range dependence everywhere but Lo's modified rescaled range test shows an absence for all contracts except for sugar. Finally, Crato and Ray (2000) examine returns data on 11 U.S. contracts, including those studied by Corazza et al. (1997) and find no evidence, and Turvey (2007) finds little evidence of long-range dependence in 13 U.S. and four Canadian futures returns.[2] A reason for these alternative conclusions is different sample sizes where larger samples are more likely to display an absence of long-range dependence (Turvey 2007). Nevertheless, Couillard and Davison (2005) observe that long-range dependence "...is anathema to financial theory. Were this possible... people would do it and in so doing remove the statistical regularity which allowed the arbitrage in the first place."

This article uses the rescaled range test of Hurst (1951) to examine the presence of long-range dependence in the returns from five wheat futures contracts, two in Europe, and three in the United States. The estimated Hurst exponent is biased and its distribution is unknown, and a Monte Carlo simulation approach is proposed to address these criticisms.

2. Empirical method

The rescaled adjusted range (or range over standard deviation) analysis of Hurst (1951) measures long memory in a stochastic time series, and amongst other methods, can be used to estimate the Hurst exponent. *Inter alia*, Mandelbrot and Wallis (1969), Mandelbrot (1972), and Mandelbrot and Taqqu (1979) argue for its superiority and it has gained recent popularity (see, e.g., Willinger et al., 1999; Jin and Frechette, 2004a, 2004b; Turvey, 2007).

Denote a discrete time series as X_i for $i = 1, \ldots N$. For $n < N$ and $n \geq 1$, the partial sum is: $Y(n) = \sum_{i=1}^{n} X_i$ and the sample variance is: $S^2(n) = n^{-1} \sum_{i=1}^{n} (X_i - n^{-1} Y(n))^2$. The (dimensionless) rescaled adjusted range statistic, R/S, is the range of partial sums of deviations of the series from its mean, rescaled by its standard deviation:

$$\frac{R}{S}(n) = \frac{1}{S(n)} \left[\underset{0 \leq t \leq n}{\text{Max}}\, Z(t) - \underset{0 \leq t \leq n}{\text{Min}}\, Z(t) \right], \tag{1}$$

where $Z(t) = (Y(t) - \frac{t}{n} Y(n))$, Max $Z(t)$ is the maximum of the partial sums $Y(n)$, and Min Z(t) is the corresponding minimum. The term, [Max $Z(t)$ – Min $Z(t)$] is the range, and since both elements are nonnegative, $R/S \geq 0$.

The classical R/S-statistic in (1) for each increment of time, n, is used to estimate the Hurst exponent, H. To illustrate, consider a series, X_i, with a sample size of $N = 5{,}000$ and time increment of $n = 5$. The series can be divided into 1,000 nonoverlapping blocks.[3] For each block, calculate the R/S-statistic and average over all blocks. This is the R/S-statistic for $n = 5$. This process is repeated for all other values of n to $N/2$ when the blocks overlap. The stability of the R/S-statistic decreases as the value of the increment increases because there are fewer observations over which to average. Finally, the following relationship is estimated by ordinary least squares (OLS):

$$\log(R/S) = H.\log(n) + \log(c) + u, \tag{2}$$

where log is to the base 10, c is a constant with no particular meaning, and u is an error term with the usual properties. The estimate of H is the Hurst exponent, which is robust to highly non-Gaussian distributions of X_i. A graphical representation of H is the "pox plot" where values of log(R/S) are plotted against those of log(n). This plot provides further information on long-range dependence and, in particular, the value of log(n) where R/S becomes more random and erratic indicates the average cycle length within the series.

The Hurst exponent, $0 < H < 1$, is the correlation between events across time. It represents the probability that two consecutive events are likely to occur (Peters, 1991, p. 67), and there are three classifications, namely $0 < H < 0.5$, $H = 0.5$, and $0.5 < H < 1$. If X_i is a random walk where the observations are independent and there is no correlation between one data value and any future value, then $H = 0.5$ and the series has no long memory. Here, there is support for the efficient market hypothesis, which implies that the present does not influence the future

[2] Crato and Ray (2000) and Jin and Frechette (2004a) find much evidence of long-range dependence in the volatilities of returns.

[3] Ellis (2007) shows that overlapping blocks are preferable for short time series, but this is not the case here.

and there is a 50% probability that X_i will increase or decrease. Such series are difficult to predict. When $H \neq 0.5$, there is a long memory effect and the order of X_i is important. In this case, X_i is a trend with noise where observations are not independent and each carries a long memory of all past observations, which in theory last forever.[4] If $0 < H < 0.5$, X_i exhibits "anti-persistent" behavior and X_i reverses itself so that an increase tends to be followed by a decrease and *vice versa*; as $H \to 0$, the correlation between successive observations is greater and reversion becomes stronger. Anti-persistent behavior is not mean-reverting because this requires a stable mean. Finally, if $0.5 < H < 1$, X_i exhibits "persistent" or trend reinforcing behavior. Since X_i is trending, an increase in X_i tends to be followed by a further increase and *vice versa*. As $H \to 1$, the stronger is the trend and such series are easier to predict; conversely as $H \to 0.5$, the noisier is the series and the less definite is the trend. If for example, $H = 0.6$, there is a 60% probability that a positive return in one period is followed by a positive return in the next.

The asymptotic distribution of the range of the sum of independent and identically distributed random variables, that is Brownian motion, has been studied for many years. Feller (1951, equations 1.4 and 1.6) shows that the expected range increases with the square root of series length, and this is what is obtained from (2) with $H = 0.5$. Feller draws attention to Hurst's empirical work showing that in real data there may not be asymptotic independence as the square root law often does not seem to apply, but instead the mean range increases more like a different power of series length. This power is the Hurst exponent. One way to interpret the Hurst exponent is through fractional Brownian motion, fBm, which is a long memory modification of a standard Brownian motion process when $H \neq 0.5$. If $H > 0.5$, the increments of fBm are positively correlated, and if $H < 0.5$, the increments are negatively correlated (Mandelbrot and Van Ness, 1968). The discrete time version of fBm is fractionally differenced white noise. In many analyses of financial series, prices are first differenced, that is $d = 1$, to yield apparently stationary returns. However, Granger and Joyeux (1980) and Hoskins (1981) examine fractional integration where d is a noninteger and this led to the development of autoregressive fractionally integrated moving average models. The fractional differencing parameter is related to the Hurst coefficient as $d = H - 0.5$. Baillie (1996) provides a survey and review of long-range dependence and fractional integration in econometrics.

There are two criticisms of rescaled adjusted range analysis. First, Davies and Harte (1987) show that it is biased toward rejecting the null of no long-range dependence for random time series, and a number of studies have recognized this bias. For example, Jin and Frechette (2004b) perform Monte Carlo experiments on repeated random samples of N observations varying from 1,000 to 10,000 and find that $\bar{H}_{MC} \approx 0.53$, where $\bar{H}_{MC}$ is the mean of H from repeated samples. In a similar experiment, Granero et al. (2008) find that $\bar{H}_{MC}$ varies between 0.68 and 0.50 and that $\bar{H}_{MC} \to 0.5$ as N and/or n increases. Thus, it is inappropriate to use a t-test to test the null of no long-range dependence where $H = 0.5$. A second and related issue is that the distribution of H is unknown (see e.g., Taqqu et al., 1995).

To address these criticisms, Lo (1991) develops a modified R/S-statistic to test the null of no long-range dependence. This modification concerns $S(n)$ in (1). Since R/S is sensitive to short-range dependence, R is normalized with a weighted sum of short-lag autocovariances. Specifically, weighted autocovariances up to order q are added to the variance, S^2. Teverovsky et al. (1999) cite two criticisms of Lo's modified R/S-statistic: first, its value depends on q, although data-driven selection methods like that of Andrews (1991) can be used; and second, for larger time series, N, and larger q, the null is less likely to be rejected, while for small q, the modified R/S-statistic varies substantially.

More recently, criticisms of the Hurst exponent have been addressed *inter alia* by Karytinos et al. (1999), Weron (2002), Jin and Frechette (2004b), Ellis (2007), and Turvey (2007) who use Monte Carlo simulation methods to calculate confidence intervals. This broad approach is used here to test the null of no long-range dependence. First, H is estimated from (2) from the actual futures returns series. Second and for the same sample size, 10,000 random series are generated with mean zero and variance equal to unity. To ensure that the random numbers in each series are truly random, a new set of "random-numbers" is redrawn with the criterion is that the first four autocorrelations are all equal to zero, and if the significance level for the Ljung–Box statistic, $Q(4) < 0.05$, a new set of pseudo-random numbers is redrawn. Third, H_{MC} is estimated for each of the 10,000 draws, and their mean, $\bar{H}_{MC}$, is the simulated Hurst exponent when returns are random. In theory, $\bar{H}_{MC} = 0.5$ but the difference, $\bar{H}_{MC} - 0.5$, provides evidence of bias when H is estimated from random returns. Finally, the null of no long-range dependence is then tested by comparing the estimated H-value from the actual returns series with the 0.025 and 0.975 fractiles, which are calculated from estimates of H_{MC} from the 10,000 draws. These confidence intervals are specific to the sample size.

To validate these results, bootstrap simulations are also undertaken following Willinger et al. (1999). In contrast with the Monte Carlo simulations, which are generated from a standard normal distribution, bootstrap simulations are drawn from an actual returns series, that is, from an observed distribution. Here, the Hurst exponent using bootstrap simulation, H_B, is calculated for each of 10,000 draws of nonoverlapping block reshuffling of actual returns. Their mean, $\bar{H}_B$, is the simulated Hurst exponent when returns are random. Confidence intervals are then calculated as above and are specific to sample size. The null of no long-range dependence is tested as before.

[4] The decay pattern of a time series with short-term (or Markovian) memory is geometric whereas that with a long-term memory is hyperbolic. Where $H < 0.5$, short memory is present but this does not preclude long memory (Lo, 1991; Turvey, 2007).

3. Data and results

The data are five daily wheat futures prices and correspond to nearby contracts (source: HGCA, 2009). Two are European contracts, one on the Euronext/London International Financial Futures and Options Exchange (LIFFE) and the other on the Marché à Terme International de France (MATIF) in Paris. The LIFFE contract is for feed wheat while the MATIF contract is for milling wheat, and both connect logistically. The other three are U.S. contracts, on the Chicago Board of Trade (CBOT), the Kansas City Board of Trade (KCBT), and the Minneapolis Grain Exchange (MGEX). The CBOT contract is for standard world soft milling wheat (Soft Red Winter, No.2, Chicago), which is used in North America and elsewhere. The KCBT and MGEX contracts are for hard, high protein milling wheat (Hard Red Winter, No.2, Kansas and Hard Red Spring, respectively), which determine the price of high quality bread wheat. Prices are measured in £/tonne on the LIFFE, €/tonne on the MATIF, and U.S. cents/bushel on the CBOT, KCBT, and MGEX. Starting dates are: LIFFE—1 August, 1991; MATIF—5 July, 1996; CBOT—5 January, 1978; Kansas KCBT—23 April, 1979; and MGEX—27 June, 1995. The end date for all series is 3/4 July, 2008. The U.S. data begin no earlier than late 1970s, which is late enough to avoid a period during which there were significant distortions due to price support.

Plots of the price data are shown in Fig. 1. On the two European markets, prices generally trend downward until mid 2007. On the LIFFE, this was caused by adverse exchange rates, which eroded U.K. export competitiveness. Spikes are evident in November/December 2003, on the LIFFE at £116/tonne and on the MATIF at €165/tonne following drought in Europe in May/July. On the U.S. markets, prices are more stable up until around mid 2007 but spikes are evident in May, 1996, on the CBOT at 717 cents/bushel and on the KCBT at 734 cents/bushel following low world production.[5] Like many commodity prices, these wheat futures prices show substantial increases from mid 2007. The most recent rise in 2008 is due to a milling wheat shortage, which triggered panic-buying in importing countries and a shortage of U.S. bread wheat, and the effect is most evident on MGEX.

Since R/S analysis is appropriate for stationary series, daily returns are analyzed, which are the (natural) logged first differences of prices. These are shown in Fig. 2 and, as expected, they show periods of increased volatility. Table 1 details samples and summary statistics. There is evidence everywhere of significant skewness and (excess) kurtosis, and Jarque-Bera (J-B) tests reject the nulls of normality: all returns are nonnormal. PP-tests (Phillips and Perron, 1988) test the null of a unit root in each return and all are stationary. This conclusion is supported by KPSS-tests (Kwiatkowski et al., 1992) where the null of stationarity is not rejected in each case.

Hurst exponents and pox plots are shown in Table 2 and Fig. 3. The straight lines in the latter have slopes of $H = 1.0$ and $H = 0.5$ and serve as reference. Hurst exponents range from 0.49 on the CBOT to 0.56 on the MATIF and evidence of long-range dependence appears weak. However, using *t*-tests, the nulls that $H = 0.5$ are rejected in all cases. Thus, there appears to be long memory in the wheat futures returns on the LIFFE, MATIF, KCBT, and MGEX where an increase tends to be followed by a further increase and *vice versa*. Conversely, returns on the CBOT exhibit anti-persistent behavior and an increase tends to be followed by a decrease and *vice versa*. From the pox plots in Fig. 3, the values of log(n) where R/S becomes more random and erratic indicate average cycle lengths. These range from around log(2.75) on the LIFFE and MATIF to log(3.25) on the CBOT, which implies average cycle lengths of around 560–1780 days.

Since random series typically produce values of $H > 0.5$ and the distribution of H is unknown, the validity of these conclusions is tested using Monte Carlo simulation. For the sample size of each returns series, 10,000 random series are generated with mean zero and variance of unity, and the Hurst exponent is estimated from each draw. From these 10,000 estimates of H_{MC}, the mean, $\bar{H}_{MC}$, and 0.025 and 0.975 fractiles (or 95% confidence intervals) are calculated. Table 2 shows the $\bar{H}_{MC}$-estimates, which range from 0.557 on the MATIF, which has the smallest sample, to 0.542 on the CBOT, which has the largest,[6] and testing the null of no long-range dependence where $H = 0.5$ in (2) is inappropriate. Table 2 also shows the 95% confidence intervals for the simulated distribution of H_{MC}-values. In all cases except for returns on the CBOT, the estimate of H from actual returns lies within these intervals leading to the conclusion that there is no long-range dependence in wheat futures returns on the LIFFE, MATIF, KCBT, and MGEX. These conclusions contrast with those from naively testing the null that $H = 0.5$ using the *t*-test in (2) where long memory is found. By contrast, there is mild evidence of anti-persistent behavior of returns on the CBOT. However, the 99% confidence intervals from Monte Carlo simulations on the CBOT are 0.484 and 0.601, which imply no long-range dependence.

For each returns series, Table 2 also shows the estimated mean Hurst exponent from bootstrap simulation, $\bar{H}_B$, and the associated 95% confidence intervals. In general, mean estimates of the Hurst exponent from Monte Carlo simulations are higher than those from bootstrap simulations, that is $\bar{H}_{MC} > \bar{H}_B$, and the 95% confidence intervals for the former are narrower. In all cases, estimates of H from actual returns lie within the bootstrap confidence intervals and there is no evidence of long-range dependence.

As Figs. 1 and 2 show, the period from around June 2007 was a commodity bull cycle that affected all wheat futures prices, and there is an increased volatility in some returns, particularly on the LIFFE following an EU policy announcement that

[5] The 1996 world shortage was muted within the EU by the residual effect of import levies and the later imposition of export levies.

[6] These estimates are higher than those of Jin and Frechette (2004b) where $\bar{H}_{MC} \approx 0.53$ on average.

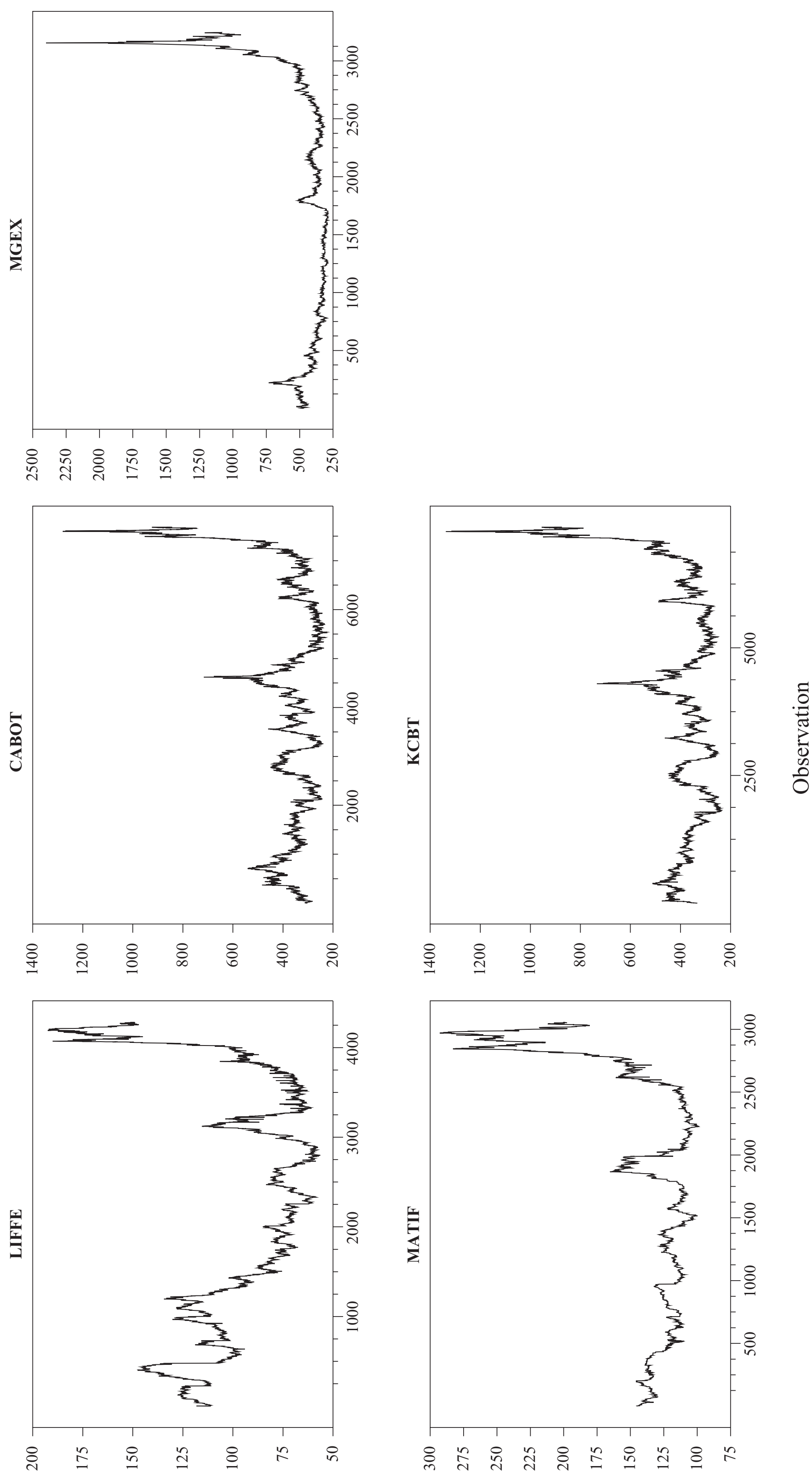

Fig. 1. Prices.

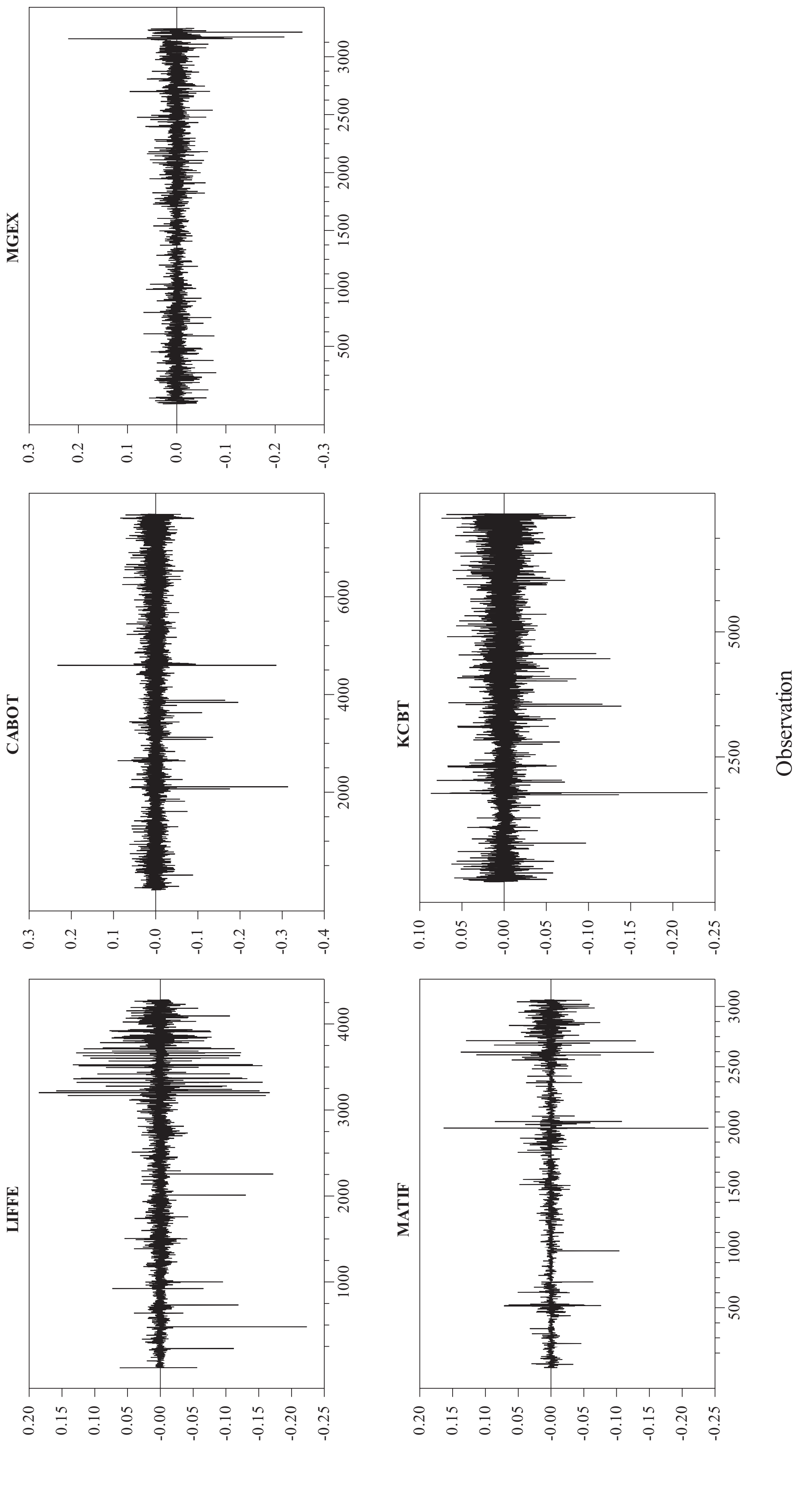

Fig. 2. Returns.

Table 1
Summary statistics for returns

	Sample	Periodicity	Obs.	Mean	SD	Min.	Max.	Skewness	Kurtosis	J-B test	PP-test	KPSS-test
Futures returns												
LIFFE	2 August, 1991– 4 July, 2008	Daily	4281	0.0001	0.0171	−0.22	0.19	−1.20 [0.00]	38.37 [0.00]	263698 [0.00]	−83.31 (lags = 1)	0.28
MATIF	6 July, 1996–4 July, 2008	Daily	3055	0.0001	0.0133	−0.24	0.16	−1.53 [0.00]	66.97 [0.00]	572041 [0.00]	−88.34 (lags = 1)	0.27
CBOT	6 January, 1978–3 July, 2008	Daily	7686	0.0001	0.0174	−0.31	0.23	−1.48 [0.00]	33.96 [0.00]	372041 [0.00]	−79.80 (lags = 1)	0.13
KCBT	24 April, 1979–3 July, 2008	Daily	7363	0.0001	0.0148	−0.24	0.09	−0.96 [0.00]	15.84 [0.00]	78139 [0.00]	−79.80 (lags = 1)	0.16
MGEX	28 June, 1995–3 July, 2008	Daily	3245	0.0003	0.0180	−0.26	0.22	−1.01 [0.00]	28.30 [0.00]	108802 [0.00]	−54.56 (lags = 1)	0.38
Cash returns												
U.K.	11 January, 1990–3 July, 2008	Weekly	966	0.0003	0.0262	−0.24	0.23	−1.30 [0.00]	20.36 [0.00]	16956 [0.00]	−29.20 (lags = 2)	0.27
Chicago	2 July, 1996–3 July, 2008	Daily	3011	0.0002	0.0200	−0.14	0.09	0.04 [0.34]	2.62 [0.00]	864.45 [0.00]	−52.92 (lags = 1)	0.37
Kansas	2 March, 2000–3 July, 2008	Daily	2124	0.0006	0.0192	−0.22	0.22	0.18 [0.00]	36.01 [0.00]	114751 [0.00]	−51.67 (lags = 1)	0.09

Notes: 1. p-values in square brackets.
2. The p-values for skewness and kurtosis correspond to the nulls of no skewness and no (excess) kurtosis.
3. For the PP-test, the lag window is selected according to the Bayesian Information Criterion; and the critical value at the 5% significance level is −2.86.
4. For the KPSS-test, the critical value at the 5% significance level is 0.46.

Table 2
Hurst exponents and simulations

	H	Monte Carlo simulations			Bootstrap simulations		
		$\bar{H}_{MC}$	CI_L	CI_U	$\bar{H}_B$	CI_L	CI_U
Futures returns							
LIFFE	0.539 (0.002)	0.550 (0.025)	0.501	0.601	0.503 (0.029)	0.446	0.560
MATIF	0.559 (0.002)	0.557 (0.027)	0.503	0.610	0.548 (0.036)	0.478	0.618
CBOT	0.488 (0.002)	0.542 (0.023)	0.498	0.587	0.523 (0.023)	0.478	0.569
KCBT	0.534 (0.002)	0.542 (0.023)	0.498	0.588	0.538 (0.022)	0.500	0.581
MGEX	0.549 (0.002)	0.556 (0.027)	0.504	0.608	0.559 (0.032)	0.495	0.622
Cash returns							
U.K.	0.632 (0.005)	0.584 (0.034)	0.518	0.651	-	-	-
Chicago	0.507 (0.003)	0.557 (0.028)	0.504	0.611	-	-	-
Kansas	0.528 (0.003)	0.552 (0.026)	0.503	0.603	-	-	-

Notes: 1. Standard errors in parentheses.
2. CI_L and CI_U denote lower and upper confidence intervals at the 95% level from simulations.

Common Agricultural Policy subsidies were to be decoupled. To allay fears that these occurrences may affect the results, H is re-estimated from all returns for sample periods up to 1 June, 2007, and in addition from returns on the LIFFE for a sample up to 5 February, 2004. $\bar{H}_{MC}$ and the confidence intervals are also re-estimated. These restricted samples remain large and estimates are almost identical to those from full samples. The estimates of H for samples up to 1 June, 2007 are: LIFFE—0.536; MATIF—0.563; CBOT—0.486; KCBT—0.536; and KCBT—0.556. That on the LIFFE for a sample up to 5 February, 2004 is 0.553. These H-estimates differ little from those using full samples and the conclusions of no long-range dependence are unaffected.

The analysis uses daily futures prices, which correspond to nearby contracts. Such prices are rolled over from one contract to another and discontinuities sometimes exist on or near contract dates. Accordingly, there is a risk of rollover bias. To address this concern, long-run dependence in wheat cash price returns, which are not rolled over, are examined. Data availability restricts this analysis to weekly feed wheat prices in the U.K. (source: HGCA, 2009); daily prices for Soft Red Winter, No.2 in Chicago (source: USDA, 2009); and daily prices for Hard Red Winter, Ordinary No.2 in Kansas (source: USDA, 2009).[7] Table 1 shows details and summary statistics for each returns series and there is much evidence that all cash returns are non-normal but stationary. In Table 2, Hurst exponents range from 0.51 for cash returns in Chicago to 0.63 for U.K. returns. Monte Carlo estimates of the mean Hurst exponent, $\bar{H}_{MC}$, and simulated confidence intervals are also shown in Table 2. $\bar{H}_{MC} > 0.5$ for all three cash returns and testing the null of no long-range dependence where $H = 0.5$ in (2) is again inappropriate. The estimates of H from actual cash returns lie within the simulated 95% confidence intervals and there is no long-range dependence in wheat cash returns. Rollover bias from using nearby futures prices appears unimportant.

[7] There are a number of missing observations in the two U.S. series usually in March or April when no cash wheat is available because it has already been sold from the harvest in the previous year. They have been ignored.

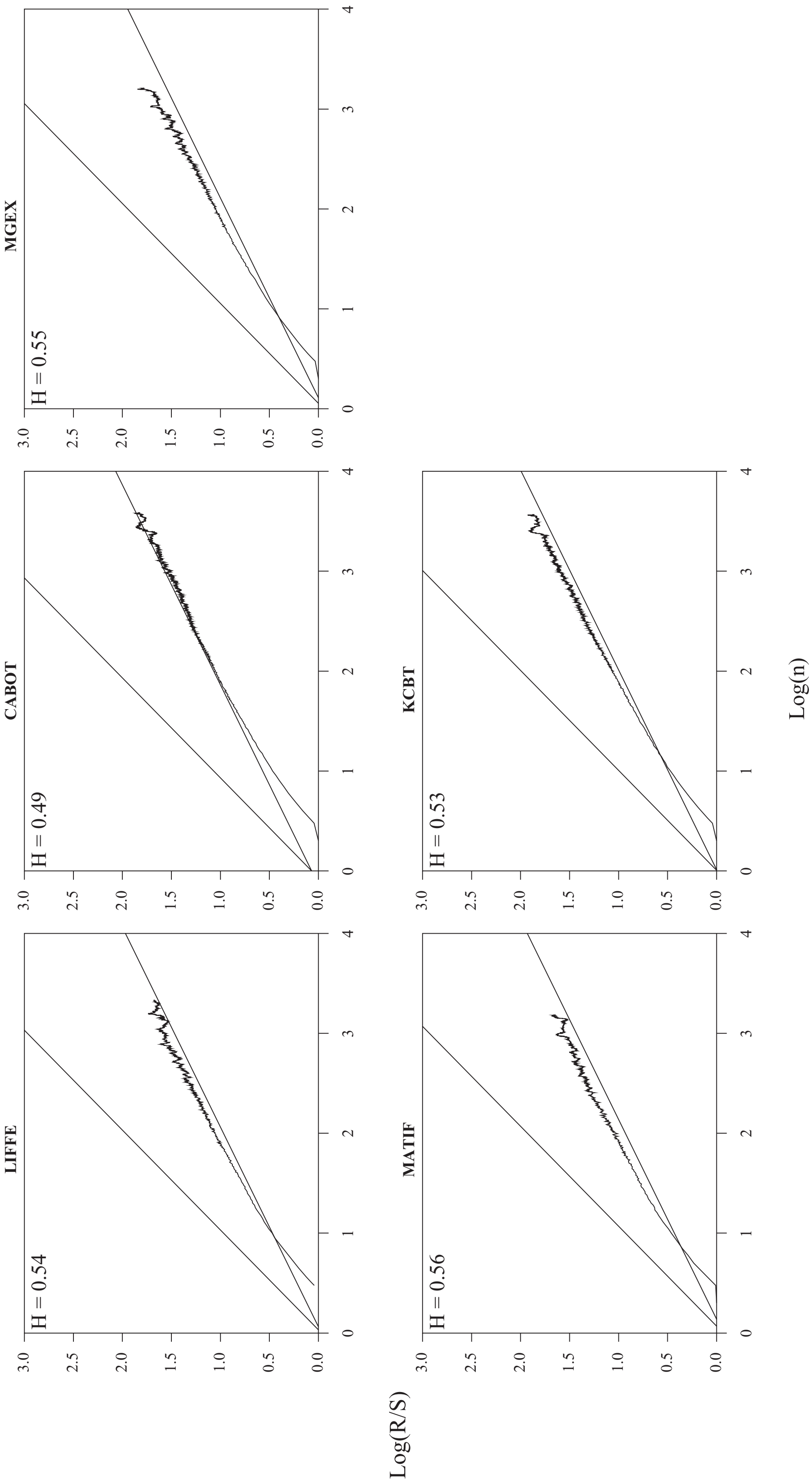

Fig. 3. R/S analysis - pox plots.

4. Summary and conclusions

The efficient market hypothesis, which is a common assumption in the financial economics literature, is where asset prices are random walks and today's price change is caused only by today's unexpected news. It implies that returns are random and long-run profits cannot be generated by predicting trends. The existence of traders however rebuffs this assumption because success depends on their ability to forecast future asset price movements. Their typical behavior in not reacting to new information immediately but waiting for a trend to be established implies that asset prices follow biased random walks.

This article examines long-range dependence in the returns to five wheat futures contracts. They are the soft wheat contracts on the LIFFE , the MATIF, and the CBOT; and the hard wheat contracts on the KCBT and the MGEX. Rescaled range analysis is used to detect long-range dependence in returns and in particular Hurst (1951) exponents, H, are calculated where $0 < H < 1$. If $H = 0.5$, the present does not influence the future, and the series has no long memory. Conversely, if $0 < H < 0.5$, returns exhibit anti-persistent behavior so that an increase tends to be followed by a decrease; and if $0.5 < H < 1$, returns exhibits persistent or trend reinforcing behavior and an increase tends to be followed by a further increase. Two criticisms of the Hurst exponent are its bias toward accepting the null of no long-range dependence, and its unknown distribution. This article proposes a Monte Carlo simulation approach to test the null of no long-range dependence. A mean H-value, $\bar{H}_{MC}$, is estimated from 10,000 random series, and a 95% confidence interval is calculated. The null of no long-range dependence is tested by comparing the estimated H-value from the actual returns with simulated confidence intervals.

Estimates of Hurst exponents range from 0.49 on the CBOT to 0.56 on the MATIF. The nulls of no long-range dependence, that is $H = 0.5$, using naive t-tests are rejected for wheat futures returns on the LIFFE, MATIF, KCBT, and MGEX and an increase tends to be followed by a further increase and *vice versa*. The null for wheat futures returns on the CBOT is also rejected; returns exhibit anti-persistent behavior and an increase in its value tends to be followed by a decrease and *vice versa*. The validity of these results is examined by Monte Carlo simulation, and in all cases except for wheat futures returns on the CBOT, the null of no long-range dependence is not rejected at the 95% confidence level. This provides further support for Davies and Harte (1987) who argue that the Hurst exponent is biased toward rejecting the null of no long-range dependence. By contrast, there is again mild evidence of anti-persistent behavior of wheat futures returns on the CBOT at the 95% confidence level but not at the 99% level. Bootstrap simulations generally produce slightly wider confidence intervals, and in each case, including returns on the CBOT, the null of no long-range dependence is not rejected at the 95% level. In summary, no evidence is found of long-range dependence in wheat futures returns and there are no profitable rules for traders and speculators.

The results presented here support the conclusions of Crato and Ray (2000) and Turvey (2007), where little evidence of persistent behavior is found in the futures returns of U.S. and Canadian agricultural commodities. However, they contrast with those of Helms et al. (1984), Corazza et al. (1997), Wei and Leuthold (2000), Jin and Frechette (2004a), and Sephton (2009) who find evidence of long-range dependence in the futures returns of U.S. agricultural commodities.

Many modern financial economics paradigms are based on the efficient market hypothesis. The result here of no long-range dependence is not contrary to this hypothesis and the insights provided by these paradigms are not compromised. As LeRoy (1989) observes, "In an efficient capital market, agents should have no investment goals other than to diversify to the maximum extent possible so as to minimize idiosyncratic risk, and to hold the amount of risk appropriate to their risk tolerance."

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