The Relationship between Spot and Futures Prices: Evidence from the Crude Oil Market

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This article examines the relationship between the spot and futures prices of WTI crude oil using a sample of daily data. Linear causality testing reveals that futures prices lead spot prices, but nonlinear causality testing reveals a bidirectional effect. This result suggests that both spot and futures markets react simultaneously to new information. © 1999 John Wiley & Sons, Inc. Jrl Fut Mark 19: 175–193, 1999

INTRODUCTION

The objective of this article is to examine the lead–lag relationship between spot and futures crude oil prices using both linear and nonlinear

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causality testing. Several studies have dealt with the lead–lag relationships between spot and futures commodity prices with the objective of examining issues such as price discovery and market efficiency. For example, Garbade and Silber (1983) present a model to examine the price discovery role of futures prices and the effect of arbitrage on price changes in spot and futures commodity markets. Several researchers have applied the Garbade-Silber model to other commodity markets such as Oellermann et al. (1989) and Schroeder and Goodwin (1991), who examined the feeder cattle market and the live hog market, respectively. Similar studies have examined the oil market. Bopp and Sitzer (1987) tested the hypothesis that futures prices are good predictors of spot prices in the heating oil market. Serletis and Banack (1990) tested for market efficiency using cointegration analysis. Crowder and Hamed (1993) also used cointegration to test the simple efficiency hypothesis and the arbitrage condition for crude oil futures. Finally, Schwarz and Szakmary (1994) examined the price discovery process in the markets for crude oil, heating oil and unleaded gasoline.

The existing empirical evidence is invariably based on conventional (linear) Granger causality testing, which has been shown to have a low power against nonlinear causality (for example, Hiemstra and Jones, 1994). Recent work, however, has revealed the existence of nonlinear structure in the process generating spot and futures returns. These nonlinearities are normally attributed to nonlinear transaction cost functions, the role of noise traders, and to market microstructure effects (Abhyankar, 1996). Moreover, it is now widely accepted, albeit controversial, that the relationships between economic and financial time series are mainly nonlinear.[1] As a result, testing for nonlinear causal relationships between two time series has received considerable attention in the recent literature. This study employs the nonlinear causality test proposed by Baek and Brock (1992).

THEORETICAL CONSIDERATIONS AND EXISTING EMPIRICAL EVIDENCE

Claims that futures trading may accentuate price fluctuations in the spot market are frequently echoed in various forums, particularly when there has been some sort of financial crisis. The underlying belief, in this respect, is that futures prices influence spot prices but not vice versa. The main argument for the hypothesis that futures prices lead spot prices is that the former respond to new information more quickly than the latter

[1]See, for example, Granger and Terasvirta (1993) and Tong (1990).

due to lower transaction costs and ease of shorting. This point may be illustrated with reference to the oil market. If new information indicates that oil prices are likely to rise,[2] a speculator has the choice of either buying crude oil futures or spot. Although the futures transaction can be implemented immediately with little up-front cash, spot purchases require a greater initial outlay and may take longer to implement. It is also arguable that speculators prefer to hold futures contracts because they are not interested in the physical commodity per se. Futures positions possess the additional advantage of ease of offset. Furthermore, hedgers who are interested in the physical commodity and have storage constraints will hedge themselves by buying futures contracts. Therefore both hedgers and speculators will react to the new information by indulging in futures rather than spot transactions. Spot prices will react with a lag because spot transactions cannot be executed so quickly.

The second argument for the hypothesis that futures prices lead spot prices is that futures markets perform the function of price discovery—as pointed out by Garbade and Silber (1983).[3] The essence of this function is to establish a competitive reference (futures) price for a commodity from which the spot price can be (subsequently) derived. The available empirical evidence on the function of price discovery is mixed. Garbade and Silber (1983) found evidence for seven commodity markets indicating that, although futures markets dominate spot markets, the latter do not just echo the former. Quan (1992) examined the price discovery function in the crude oil market and concluded that the futures price does not play a very important role in the price discovery process. Schwarz and Szakmary (1994) question Quan's conclusion by wondering why futures markets continue to flourish if they do not provide "one of the essential tenants for their existence", referring to the price discovery function. Their empirical results, which are based on high frequency data, suggest that crude oil futures markets dominate the spot markets in price discovery. They attribute Quan's failure to find support for the price discovery function of the futures market to the (inappropriate) choice of data and time interval. Further evidence for the price discovery role is provided by Schroeder and Goodwin (1991) and by Bopp and Sitzer (1987).

Futures trading can also facilitate the allocation of production and consumption over time, particularly by providing market guidance in the holding of inventories (Houthakker, 1992, p. 212). If, for example, fu-

[2]Perhaps because of a serious decision by OPEC to restrict production, an impending harsh winter, a spectacular economic recovery in industrial countries, or another adventure by Saddam Hussein.
[3]See also Houthakker (1992, p. 212) and Newberry (1992, p. 210). Newberry describes futures markets as "potent institutions for price discovery."

tures prices for distant deliveries are well above those for early deliveries, postponement of consumption becomes attractive. Thus changes in futures prices result in subsequent changes in spot prices arising from changes in the spot demand for the commodity.

Newberry's (1992, p. 210) postulation that futures markets provide opportunities for market manipulation, suggests another argument for the hypothesis. According to this argument, the futures market can be manipulated either by the better informed at the expense of the less informed or by the larger at the expense of the smaller. For example, OPEC may find it profitable to intervene in the futures market to influence the production decisions of their competitors in the spot market. Again, the implied causality runs from futures to spot prices.

Support for the hypothesis that futures prices lead spot prices can also be found in the model of determination of futures prices proposed by Moosa and Al-Loughani (1995). In this model the futures price is determined by (i) arbitrageurs whose demand for futures contracts depends on the difference between the arbitrage price (as determined by the cost-of-carry equation) and the actual futures price; and (ii) speculators whose demand depends on the difference between the expected spot price and the actual futures price. The reference point in both cases is the futures price and not the spot price. When there is information indicating that oil prices are expected to rise in the future, speculators will react by changing their demand for futures contracts. As a result, the cost-of-carry condition will be violated, triggering action from arbitrageurs who act in the spot and futures markets, thus changing the spot price in such a way as to restore the cost-of-carry condition. In Moosa's (1996) extension of this model speculation takes place with no direct reference to the spot market, as the demand by another class of speculators depends on the difference between the current futures price and the futures price expected to prevail in the future.

On the other hand, it is possible to trace the sequence of events that follow a change in spot prices caused by a change in demand by participants who are unwilling to or incapable of dealing in the futures market. The change in the spot price will trigger action from the three kinds of market participant in the Moosa (1996) model, and these actions will (subsequently) change the futures price. First of all, arbitrageurs will react to the violation of the cost-of-carry condition. Second, speculators who act upon the expected spot price will revise their expectation and respond to the disparity between the futures price and the expected spot price. Likewise, speculators who act upon the expected futures price will revise their expectation and respond to the disparity between the current futures price and the expected futures price. In this case spot prices lead futures prices.

Considering the relationship between spot and futures stock prices, Kawaller et al. (1988) put forward the general principle that spot prices are affected by their past history, current and past futures prices, and other market information. Likewise, futures prices are affected by their past history, current and past spot prices and other market information. Thus causality is likely to be bidirectional. They further argue that potential lead and lag patterns between futures and spot prices are subject to change as new information arrives. Each may lead the other, as market participants sift the information for clues that are relevant to their positions, which may be spot or futures. Indeed, they present evidence indicating that lags not only exist between movements in futures prices and subsequent movements in the spot prices but also vice versa. There is no reason why this argument is not valid for the oil market as well.

The conclusion that can be derived from the discussion so far is that there is some rationale and empirical evidence for the hypothesis that futures prices lead spot prices and also for the hypothesis that spot prices lead futures prices. However, the case for the first hypothesis is stronger and more compelling. Hence, further empirical testing is required to resolve, or at least to shed some light on, this issue as applied to the crude oil market.

LINEAR CAUSALITY TESTING: THE HSIO PROCEDURE

In this section we define causality and briefly describe Hsio's (1981) sequential procedure for linear Granger causality testing between two stationary series, x and y. Let $\{x_t\}$ and $\{y_t\}$ be two series and $F(x_t|\phi_{t-1})$ be the conditional probability distribution of $\{x_t\}$ given the information set ϕ_{t-1} which is defined as:

$$\phi_{t-1} = \{x_{t-\ell x}^{\ell x}, y_{t-\ell y}^{\ell y}\} \tag{1}$$

such that

$$x_{t-\ell y}^{\ell x} = \{x_{t-\ell x}, x_{t-\ell x-1}, \ldots, x_{t-1}\} \tag{2}$$

and

$$y_{t-\ell y}^{\ell y} = \{y_{t-\ell y}, y_{t-\ell y-1}, \ldots, y_{t-1}\} \tag{3}$$

where ℓx and ℓy are the lag lengths of x_t and y_t respectively. Given ℓx and ℓy, $\{y_t\}$ does not Granger cause $\{x_t\}$ if

$$F(x_t|\phi_{t-1}) = F[x_t|(\phi_{t-1} - y_{t-\ell y}^{\ell y})] \tag{4}$$

If eq. (4) does not hold, then knowledge of past y values helps to predict current and future x values, and y is said to cause (in a Granger sense) x strictly. Similarly, if

$$F(x_t|\phi_{t-1}) = F[x_t|(\phi_{t-1} + y_t)] \tag{5}$$

where the information set is modified to include the current value of y, then there is a lack of instantaneous causality from y to x. On the other hand, if eq. (5) does not hold, then y is said to cause x instantaneously. In this study, we focus on testing for strict Granger causality alone due to problems in distinguishing between instantaneous causality and instantaneous feedback relations.

Causality testing is based on the bivariate VAR representation:

$$x_t = \alpha_0 + \sum_{i=1}^{\ell x} \alpha_i x_{t-i} + \sum_{j=1}^{\ell y} \beta_j y_{t-j} + u_{x,t} \tag{6}$$

$$y_t = \beta_0 + \sum_{i=1}^{\ell x} \alpha_i x_{t-i} + \sum_{j=1}^{\ell y} \beta_j y_{t-j} + u_{y,t} \tag{7}$$

where x and y are stationary variables. The null hypothesis in the Granger causality test is that y does not cause x which is represented by, $H_0{:}\beta_1 = \cdots = \beta_{\ell y} = 0$, whereas the alternative hypothesis is $H_1{:}\beta_j \neq 0$ for at least one j in (6). The test statistic has a standard F distribution with $(\ell x, T - \ell x - \ell y - 1)$ degrees of freedom where T is the sample size. Obviously, the value of the test statistic depends on ℓx and ℓy which makes it necessary to use various information criteria to choose the optimum lag lengths.[4] Testing for causality from x to y is based on eq. (7).

Hsio (1981) has suggested a sequential procedure for causality testing that combines Akaike's final predictive error criterion (FPE) and the definition of Granger causality. Testing for causality from y to x consists of the following steps:

1. Treat x as a one-dimensional process as represented by eq. (6) with $\beta_j = 0\ \forall j$, and compute its FPE with ℓx varying from 1 to L, which is chosen arbitrarily. Choose the ℓx which gives the smallest FPE, denoted $FPE_x(\ell x, 0)$.

[4]If x_i and y_t are I(1) and cointegrated, then eqs. (6) and (7) must be respecified in terms of first differences, including error correction terms.

2. Treat x as a controlled variable, with ℓx as chosen in step 1 and y as a manipulated variable as in eq. (6). Compute the FPEs of eq. (6) by varying the order of lags of y from 1 to L and determine ℓy which gives true minimum FPE, denoted $FPE_x(\ell x, \ell y)$.
3. Compare $FPE_x(\ell x, 0)$ with $FPE_x(\ell x, \ell y)$. If the former is greater than the latter, then it can be concluded that y causes x.

NONLINEAR GRANGER CAUSALITY TESTING: THE BAEK-BROCK TEST

Before embarking on an exposition of the nonlinear causality test used in this article, it may be useful to elaborate on the issue of nonlinearities in financial time series. This discussion should provide a justification for the use of nonlinear causality testing.

Savit (1988, pp 271–272) argues that financial and commodity markets are likely to be examples of dynamical systems manifesting nonlinearities. He disputes the argument that fluctuations in detrended price series are random and argues instead that these fluctuations are generated by "inherent nonlinearities." The distinction between linear and nonlinear adjustment to any deviation from the equilibrium price or return lies in whether or not the magnitude of adjustment is proportional to the deviation. A proportional adjustment implies a linear relationship, but this kind of adjustment cannot generate the kind of "random" behavior often observed in these markets. Savit (1988) argues that nonlinear adjustment can produce this kind of behavior. Moreover, he suggests that nonlinear adjustment arises from market psychology because "the complexities do not average out to produce linear correction." Hsieh (1991) puts forward a similar point by arguing that large moves in prices, which are greater than what is expected under a normal distribution, may be attributed to nonlinearities. Savit (1989) also argues that nonlinearities (for which there is a good deal of evidence) elude common (linear) statistical tests.

The Baek-Brock (1992) nonparametric test, as modified by Hiemstra and Jones (1994), is designed to detect nonlinear causal relations that cannot be detected by traditional linear causality tests. This test is based on the concept of the correlation integral, which is an estimator of spatial probabilities across time.

Let $\{x_t\}$ and $\{y_t\}$ be two strictly stationary and weakly dependent time series, x_t^m be the m-length lead vector of $\{x_t\}$ defined as $x_t^m = \{x_t, x_{t+1}, \ldots, x_{t+m-1}\}$. For $m \geq 1$, $\ell x \geq 1$, $\ell y \geq 1$ and $e > 0$, y does not strictly Granger cause x if

$$\Pr(\|x_t^m - x_s^m\| < e \mid \|x_{t-\ell x}^{\ell x} - x_{s-\ell x}^{\ell x}\| < e,\ \|y_{t-\ell y}^{\ell y} - y_{s-\ell y}^{\ell y}\| < e)$$
$$= \Pr(\|x_t^m - x_s^m\| < e \mid \|x_{t-\ell x}^{\ell x} - x_{s-\ell x}^{\ell x}\| < e) \tag{8}$$

where Pr(.) and $\|\cdot\|$ denote the probability and the maximum norm respectively. The left side of eq. (8) is the conditional probability that two arbitrary m-length lead vectors of $\{x_t\}$ are within a small distance e of each other, given that the corresponding ℓx and ℓy (lag vectors) are within e of each other. The probability on the right side of (8) is the conditional probability that two arbitrary m-length lead vectors of $\{x_t\}$ are within a distance e of each other.

By expressing the conditional probabilities in terms of the corresponding ratios of joint probabilities in eq. (8), we obtain

$$\frac{C1(m + \ell x, \ell y, e)}{C2(\ell x, \ell y, e)} = \frac{C3(m + \ell x, e)}{C4(\ell x, e)} \tag{9}$$

where

$$C1(m + \ell x, \ell y, e) = \Pr(\|x_{t-\ell x}^{m+\ell x} - x_{s-\ell x}^{m+\ell x}\| < e,\ \|y_{t-\ell y}^{\ell y} - y_{s-\ell y}^{\ell y}\| < e) \tag{10}$$

$$C2(\ell x, \ell y, e) = \Pr(\|x_{t-\ell x}^{\ell x} - x_{s-\ell x}^{\ell x}\| < e,\ \|y_{t-\ell y}^{\ell y} - y_{s-\ell y}^{\ell y}\| < e) \tag{11}$$

$$C3(m + \ell x, e) = \Pr(\|x_{t-\ell x}^{m+\ell x} - x_{s-\ell x}^{m+\ell x}\| < e) \tag{12}$$

$$C4(\ell x, e) = \Pr(\|x_{t-\ell x}^{\ell x} - x_{s-\ell x}^{\ell x}\| < e) \tag{13}$$

For $m \geq 1$, $\ell x \geq 1$, $\ell y \geq 1$ and $e > 0$, the strict Granger noncausality condition is given in eq. (9).

Correlation-integral estimators of the joint probabilities given by eqs. (10)–(13) are used to test the condition represented by eq. (9). For realizations of x and y, say $\{x_t\}$ and $\{y_t\}$ for $t = 1, \ldots T$, let $\{x_t^m\}$, $\{x_{t-\ell x}^{\ell x}\}$ and $\{y_{t-\ell y}^{\ell y}\}$ denote the m-length lead and ℓx-length lag vectors of $\{x_t\}$ and the ℓy-length lag vector of $\{y_t\}$ as defined previously. Let $I(z_1, z_2, e)$ be a kernel that takes the value of 1 when two conformable vectors, z_1 and z_2, are within the maximum-norm distance, e, of each other and 0 otherwise. Correlation integral estimators of the joint probabilities given by eqs. (10)–(13) can be written as:

$$C1(m + \ell x, \ell y, e, n) = \frac{2}{n(n - 1)} \sum\sum_{t<s}$$

$$I(x_{t-\ell x}^{m+\ell x}, x_{s-\ell x}^{m+\ell x}, e).\ I(y_{t-\ell y}^{\ell y}, y_{s-\ell y}^{\ell y}, e) \qquad (14)$$

$$C2(\ell x, \ell y, e, n) = \frac{2}{n(n - 1)} \sum\sum_{t<s}$$

$$I(x_{t-\ell x}^{\ell x}, x_{s-\ell x}^{\ell x}, e).\ I(y_{t-\ell y}^{\ell y}, y_{s-\ell y}^{\ell y}, e) \qquad (15)$$

$$C3(m + \ell x, \ell y, e, n) = \frac{2}{n(n - 1)} \sum\sum_{t<s} I(x_{t-\ell x}^{m+\ell x}, x_{s-\ell x}^{m+\ell x}, e) \qquad (16)$$

$$C4(\ell x, e, n) = \frac{2}{n(n - 1)} \sum\sum_{t<s} I(x_{t-\ell x}^{\ell x}, x_{s-\ell x}^{\ell x}, e) \qquad (17)$$

where $t,s = \max(\ell x,\ell y) + 1, \ldots, T + m - 1$ and $n = T + 1 - m - \max(\ell x,\ell y)$.

Using the joint probability estimators given by eqs. (14)–(17), the strict Granger noncausality condition in (8) can be tested as follows. For $m \geq 1$, $\ell x \geq 1$, $\ell y \geq 1$ and $e > 0$

$$\sqrt{n}\left(\frac{C1(m + \ell x, \ell y, e, n)}{C2(\ell x, \ell y, e, n)} - \frac{C3(m + \ell x, e, n)}{C4(\ell x, e, n)}\right)$$

$$\sim AN(0, \sigma^2 (m, \ell x, \ell y, e)) \qquad (18)$$

The nonlinear Granger causality test as represented by eq. (18) is applied to the OLS residuals of eqs. (6) and (7), which are free from linear predictive power. Baek and Brock (1992) argue that, by removing linear predictive power with a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered nonlinear predictive power. Furthermore, they find that the test applied to consistently estimated residuals also has the same distribution as in eq. (18) and that the test is robust to nuisance parameter problems. Hiemstra and Jones's (1994) results of a simulation study suggest that their modified test also has similar robust properties.

VOLATILITY MODELS

It may be necessary to eliminate the effect due to dynamic heteroskedasticity by fitting ARCH-type volatility models. This step may be necessary because it is possible that nonlinear causality could be due to simple volatility effects associated with information flows, in which case the nonlinear causality test could be merely detecting spurious causality.

The conditional variance of the series, denoted h_t, is modeled as

$$Z_t = \mu + u_t \tag{19}$$

where $u_t|\phi_{t-1} \sim N(0,h_t)$ and

$$h_t = h_0 + \sum_{j=1}^{q} a_j u_{t-j}^2 + \sum_{k=1}^{p} b_k h_{t-k} \tag{20}$$

where $t = \max(p,q), \ldots, T$. By imposing the restriction $b_1 = \cdots = b_p = 0$ on eq. (20) we obtain ARCH(q) models. Although ARCH/GARCH specifications have been found to be generally successful, there are some features of the data that these models fail to capture, the most interesting of which is the "leverage" effect (Nelson, 1991). Statistically, this effect implies that negative surprises to financial markets increase predictive volatility more than positive surprises. To capture such effects Nelson proposed the exponential GARCH model. An EGARCH (p,q) model is given by

$$\log h_t = h_0 + \sum_{k=1}^{p} c_k u_{t-k} h_{t-k}^{-1/2} + \sum_{j=1}^{q} a_j \log h_{t-j} + a[|u_{t-1}|h_{t-1}^{-1/2} - (2/\pi)^{1/2}] \tag{21}$$

where $t = \max(p,q), \ldots, T$.

Hsieh (1993) presents two reasons the EGARCH model is preferable to Engle's (1982) ARCH model or Bollerslev's (1986) GARCH model. The first reason is that the EGARCH model allows the conditional variance to respond differently to a rise than to a fall in the variance, whereas ARCH and GARCH models impose a symmetric response. The second reason is that the EGARCH model does not need the imposition of any constraint on the coefficients of the variance equation to enforce the nonnegativity of the variance.

DESCRIPTION AND TIME SERIES PROPERTIES OF THE DATA

In this section, the data series used in this study are described and the time series properties of the data are discussed. Thus the results presented in this section include those derived from testing for unit root, cointegration, and the presence of ARCH effect. These results (not reported here, in consideration of space) are available from the authors on request.

The data sample used in this study consists of daily observations of spot and futures prices of WTI crude oil covering the period between 2 January 1985 and 11 July 1996. Three futures contracts with maturities of one month, three months and six months are considered. The following notation is used: s_t is the logarithm of the spot price while f_t^{t+1} f_t^{t+3} and f_t^{t+6} are the logarithms of the futures prices for maturities of one, three and six months respectively. It must be borne in mind, however, that the use of daily data suggests that these are the maximum maturity lengths which decline as the settlement dates are approached. The data were obtained from the OPEC data base as reported by the New York Mercantile Exchange.

Testing for the stationarity of the time series is based on the Dickey-Fuller (1979) ADF test and the Kwiatkowski et al. (1992) KPSS test. The results show that both tests confirm that the four series are nonstationary. The implication of this finding is that the models used to test for causality should be specified in first differences.

The next step is to test for cointegration between spot and futures prices. This step is necessary because the results of these tests determine the specification of the model used for causality testing. If the series are cointegrated, then causality testing should be based on an error correction model rather than an unrestricted VAR as represented by eqs. (6) and (7). The results of testing for cointegration, using the ADF and KPSS tests as well as the Johansen procedure, indicate that only s_t and f_t^{t+1} are cointegrated.

Although testing for cointegration is conducted solely for the purpose of specifying the model used to test for causality, the cointegration results warrant some discussion. A finding of no cointegration between spot and futures prices is normally interpreted to imply either market inefficiency or that the (spot and futures) markets do not represent the same underlying asset. We find the first interpretation more plausible. The absence of cointegration means the violation of the necessary condition for the simple efficiency hypothesis, which implies that the futures price is not an unbiased predictor of the spot price on maturity. This follows from the absence of a long-run relationship between spot and futures prices. Several authors have reported similar results and a similar interpretation, including Krehbiel and Adkins (1993), Crodwer and Hamed (1993); and Chowdhury (1991). If the cost-of-carry relationship is the only connection between spot and futures prices, then a finding of no cointegration is attributed to the nonstationarity of the components of this relationship such as the interest rate or the convenience yield. However, if the role of speculation is introduced, the lack of cointegration can be caused by the nonstationarity of the expectation error (see Moosa and Al-Loughani, 1995, and Moosa, 1996).

One also needs to say something about the difference in the results for different maturities. A finding of cointegration for the short maturity only is supported by Quan (1992). Moosa (1996) found that speculation in the crude oil futures market is based on the price of the contract expected to prevail one month from the present time. It seems that because of uncertainty, market participants take decisions covering short time horizons. This may explain why cointegration is present in the case of short maturities only. Hence, there is some sort of a "maturity effect" with respect to market efficiency. However, what is important for this study is not cointegration, but rather temporal priority which is revealed by causality testing.

In order to detect volatility in the series, two tests are applied: Engle's (1982) LM test and the Silvapulle and Silvapulle (1995) one-sided score test. Both of these tests are applied to the first differences of the series using ARCH(4) specification. The results reveal that volatility is present in all of the series.

LINEAR AND NONLINEAR CAUSALITY TESTING: EMPIRICAL RESULTS

In this section the results of testing for linear and nonlinear causality are presented. The results of the application of Hsio's (1981) procedure to test the null that $f_t^{t+i} (i = 1,3,6)$ does not cause s_t and vice versa are reported in Table I. It is apparent that in testing the null that f_t^{t+i} does not cause s_t, the FPE of the model with Δs_t alone is considerably larger than that of the FPE of the model of Δs_t on Δf_t^{t+i} for all i. On the other hand, it can be observed that when the null that s_t does not cause f_t^{t+i} is tested, the reduction in FPE is so small that it is not statistically significant, in which case the null is not rejected for all i.[5] On the basis of these results we can conclude that there is a one-directional (linear) causality from futures prices to spot prices but not vice versa.[6] The results presented in Table I raise another implication for market efficiency. The

[5]The insignificance of the reduction in FPE is confirmed by an F test. The results of this test are not reported but are available from the authors upon request.

[6]Although cointegration implies causality in at least one direction, the absence of cointegration does not preclude causality. See Granger (1988) on the reconciliation of the concepts of cointegration and causality.

TABLE I

Testing for Linear Causality Between Spot and Futures Prices[a]

Controlled Variable (x)	ℓx	*Manipulated Variable*	ℓy	*FPE* (ℓx, 0) ($\times 10^4$)	*FPE* (ℓx, ℓy) ($\times 10^4$)	*Result*[b]
$\Delta s_t^{\#}$	42	Δf_t^{t+1}	21	6.400	6.203	C
$\Delta f_t^{t+1\#}$	24	Δs_t	24	6.047	6.029	NC
Δs_t	42	Δf_t^{t+3}	26	6.400	6.275	C
Δf_t^{t+3}	5	Δs_t	1	3.762	3.743	NC
Δs_t	42	Δf_t^{t+6}	20	6.400	6.293	C
Δf_t^{t+6}	43	Δs_t	26	2.945	2.939	NC

[a]The test is based on the first log differences of the variables.
[b]C indicates the presence of a causal relationship; NC indicates the absence of a causal relationship.
[#]Testing for causality is conducted on the basis of an error correction model.

estimates show that there are long lags except for f_t^{t+3} . This finding is in contrast with Samuelson's (1965) theoretical postulation that futures prices would follow a martingale process under the simple efficiency hypothesis. It has to be mentioned here that the empirical evidence on the market efficiency hypothesis has not been overwhelmingly supportive. This has even enforced a reconsideration of the efficiency hypothesis and the relationship between cointegration and market efficiency (see, for example, Dwyer and Wallace, 1992).

Table II reports the results of nonlinear causality testing as applied to the estimated VAR residuals represented by eqs. (6) and (7), in which the dependent variables are (the first log differences of) spot and futures prices, respectively. The results for the one-month maturity only are reported, whereas for the other two maturities they are available from the authors on request. The appropriate values for the lead–lag length m, the lag lengths ℓx and ℓy, and the scale parameter e must be chosen in order to apply this procedure. Hiemstra and Jones (1994) recommend the following values: $m = 1$, $\ell x = \ell y$ and $e = 1.5$ with $\sigma = 1$. In Table II, CS and TVAL denote the difference between two conditional probabilities as given by eq. (9) and the standardized statistic given in eq. (18), respectively. To investigate the sensitivity of the results, the value of e is varied from 1.0 to 2.0 and that of σ from 1.0 to 3.0. Only a marginal difference emerges as a result.

The results of nonlinear causality testing provide very strong evidence for the presence of bidirectional nonlinear causality effect between s_t and f_t^{t+i} for all i. This result holds for all common lag lengths used for conducting the test. The test detects nonlinear causality from s_t to f_t^{t+i}, which the linear causality test could not uncover. It can therefore be

TABLE II

Testing for Nonlinear Causality (Spot and One-Month Futures Price)[a]

	$s_t \rightarrow f_t^{t+1}$		$f_t^{t+1} \rightarrow s_t$	
$\ell x = \ell y$	*CS*	*TVAL*	*CS*	*TVAL*
1	0.012	7.241	0.016	6.128
2	0.019	6.420	0.021	5.899
3	0.021	6.018	0.032	5.672
4	0.028	5.720	0.039	5.471
5	0.030	5.689	0.048	4.992
6	0.023	5.218	0.045	4.621
7	0.018	4.999	0.038	3.928
8	0.022	4.820	0.018	3.620
9	0.020	4.601	0.019	3.000
10	0.016	4.521	0.023	2.412
11	0.014	4.310	0.025	2.468
12	0.007	4.124	0.033	2.300

[a]The results are based on the modified Baek and Brock nonlinear causality test. The test is applied to the VAR residuals corresponding to the spot and futures price changes. CS and TVAL respectively denote the difference between two conditional probabilities in equation (9) and the standardised test statistic of equation (18). Under the null hypothesis of noncausality, the test statistic has a standard normal distribution.

concluded that there is a bidirectional causality between spot and futures prices, with causality from spot to futures prices being only nonlinear in nature.

Hsieh (1991) finds that much of the nonlinear structure in daily stock prices is related to ARCH dependence. Therefore it is possible that nonlinear causality between spot and futures prices could be associated with information flow. As such, if lagged prices capture temporal dependence in the latent speed of information flow, the nonlinear test could only detect spurious causality. In the material that follows, some evidence is provided on the issue of whether the modified Baek and Brock (1992) test is influenced by the latent variable effect associated with information flow that can account for volatility persistence in spot and futures prices. In particular, some evidence is provided on the extent to which the nonlinear predictive power of futures prices for spot prices can be explained by volatility in futures prices serving as a proxy for daily information flow in the stochastic process generating the spot price variance.

NONLINEAR CAUSALITY TESTING OF THE VOLATILITY-FILTERED SERIES: EMPIRICAL RESULTS

In this section we present the results of volatility models and results of applying the modified Baek and Brock (1992) test to the volatility-filtered spot and futures prices. These models account for both linear effects and volatility.

The results of fitting ARCH-type models, as represented by eqs. (20) and (21) to the four series, are reported in Table III. The best model is selected on the basis of the Akaike and the Schwartz Bayesian information criteria, both of which consistently indicate that an EGARCH(2,1) model is appropriate for s_t and f_t^{t+1}, while an EGARCH(1,1) is appropriate for f_t^{t+3} and f_t^{t+6}. The Table reports the mean and volatility equations, including the robust t statistics (in parentheses), which are computed using the Newey-West procedure.

Table IV reports the results of testing for nonlinear causality as applied to the EGARCH-filtered spot and futures prices adjusted for linear effects. Again, the results are reported for the one-month maturity only. The modified Baek and Brock test rejects the null hypothesis of nonlinear noncausality from spot to futures prices and vice versa for many of the common lag lengths used at the 5% significance level. It is clear that the EGARCH filtering of the price series substantially reduces both the magnitude and the statistical significance of the test statistics as compared with those based on the volatility-unadjusted series (Table II). The significant difference between the two sets of results indicates that the nonlinear causality effect detected by the Baek and Brock test is partly due to simple volatility effects. Interpreting the results cautiously, it is possible to say there is strong evidence supporting the presence of a bidirectional nonlinear causality effect between spot and futures prices unrelated to volatility persistence in these prices.

CONCLUSION

The results obtained in this study have several related implications, including the following: (i) There is feedback from spot to futures prices; (ii) both markets react to new information simultaneously; and (iii) the pattern of leads and lags changes over time. Given that causality can run in one direction only at any point in time, a finding of bidirectional causality over the sample period may be taken to imply a changing pattern of leads and lags over time. These implications, which cannot be revealed by using linear causality, are consistent with some theoretical propositions that have been put forward in the literature. This study has revealed more evidence for causality from futures prices to spot prices than otherwise. Hence it can be safely concluded that, although the futures market may play a bigger role in the price discovery process, the spot market also plays a role in this respect.

TABLE III

Estimated Volatility Models (Mean and Variance Equations)[a]

Series	*Mean*	*Variance*
s_t	$Z_t = 0.060 + u_t$	$\log(h_t) = 0.007 + 0.901\ \log(h_{t-1}) + 0.021\ \log(h_{t-2}) + 0.053\ [\lvert u_{t-1}\rvert h_{t-1}^{-1/2} - (2/\pi)^{1/2}$
	(3.71)	(0.012) (16.20) (2.15) (2.71)
f_t^{t+1}	$Z_t = 0.071 + u_t$	$\log(h_t) = 0.005 + 0.906\ \log(h_{t-1}) + 0.089\ \log(h_{t-2}) + 0.028[\lvert u_{t-1}\rvert h_{t-1}^{-1/2} - (2/\pi)^{1/2}$
	(4.32)	(1.12) (14.80) (3.40) (2.15)
f_t^{t+3}	$Z_t = 0.068 + u_t$	$\log(h_t) = 0.007 + 0.899\ \log(h_{t-1}) + 0.039[\lvert u_{t-1}\rvert h_{t-1}^{-1/2} - (2/\pi)^{1/2}]$
	(4.72)	(1.62) (17.20) (3.42)
f_t^{t+6}	$Z_t = 0.070 + u_t$	$\log(h_t) = 0.010 + 0.897\ \log(h_{t-1}) + 0.043[\lvert u_{t-1}\rvert h_{t-1}^{-1/2} - (2/\pi)^{1/2}]$
	(4.92)	(1.72) (19.00) (4.32)

[a]Figures in parentheses are the t statistics.

TABLE IV

Testing for Nonlinear Causality (Volatility-Filtered Spot and One-Month Futures Prices)[a]

	$s_t \rightarrow f_t^{t+1}$		$f_t^{t+1} \rightarrow s_t$	
$\ell x = \ell y$	*CS*	*TVAL*	*CS*	*TVAL*
1	0.009	3.968	0.010	3.139
2	0.016	3.953	0.014	2.869
3	0.015	2.967	0.018	2.242
4	0.017	2.821	0.018	2.140
5	0.015	2.601	0.021	1.982
6	0.016	2.402	0.022	1.828
7	0.013	2.272	0.016	1.620
8	0.009	2.270	0.006	1.520
9	0.014	2.126	0.009	1.320
10	0.013	1.520	0.010	1.301
11	0.007	1.162	0.012	0.928
12	0.004	1.003	0.016	0.820

[a]The test is based on the volatility filtered prices using the residuals from the VAR specification of volatility filtered spot and futures price changes. The values of m and e are 1 and 1.5 respectively. The null hypothesis is noncausality.

There are some caveats that must be taken into account while interpreting the results of this study. The first caveat concerns the concept of Granger causality, which does not imply a cause and effect relationship in the strict sense, but rather implies econometric exogeneity. Granger (1990, p. 45) points out that causality "is not the same for all economists." Causality, as used in this article and in similar empirical studies, is based on temporal priority in the sense that the cause cannot occur after the effect. This concept is, however, suitable for the purpose of this study. It is temporal priority, and not causality in the strict sense, that determines whether the spot market, the futures market, or both perform the function of price discovery.[7] Second, it may be argued that the frequency of the data may affect the results of causality testing. This argument is normally put forward against the use of low-frequency data on the grounds that it may conceal causality or the "true" lead–lag relationship. On this occasion the argument may be used against employing daily data and for transaction-by-transaction intraday data. Although this argument may be valid, the use of daily data is the best available option if intraday data are not available. Indeed, most similar studies are based on daily data. Moreover, the results reveal, rather than conceal, the presence of bidirectional nonlinear causality. It remains to be seen, however, if the use of intraday data produces different results such as supporting bidirectional linear causality. Third, and finally, the notion that financial and commodity market prices are generated from nonlinear processes remains controversial and should be treated as such. Although a random behavior may be taken as evidence for the presence of nonlinearities, there is a large amount of evidence against the random walk hypothesis.

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[7]For further elaboration on the concept of causality, see Drakopoulos and Torrance (1994).

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