The lead-lag relationships between spot and futures prices of natural gas

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HIGHLIGHTS

- We employ both linear and nonlinear causality tests.
- We find linear causality from futures to spot prices.
- We find bidirectional causality between spot and futures prices.
- Volatility spillover can partly explain the nonlinear causality behavior.
- The cross-correlations are also analyzed.

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ABSTRACT

The lead-lag relationships between spot and futures markets are of great interest for academics. Previous studies neglect the possibility of nonlinear behaviors which may be caused by asymmetry or persistence. To fill this gap, this paper uses the MF-DCCA method and the linear and nonlinear causality tests to explore the causal relationships between natural gas spot and futures prices in the New York Mercantile Exchange. We find that spot and futures prices are positive cross-correlated, the natural gas futures can linearly Granger cause spot price, and there are bidirectional nonlinear causality relationships between natural gas spot and futures prices. Further, we explore the sources of nonlinear causality relationships, and find that the volatility spillover can partly explain the nonlinear causality and affect their cross-correlations.

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1. Introduction

Natural gas is the cleanest fossil fuel, its carbon emissions are much lower than those of coal and oil, and other pollutants are emitted less. With the increasing awareness of energy conservation, the study of natural gas price is gradually important. As a market form of high-class, the natural gas futures market has been widely adopted by the developed countries due to its price discovery and hedging function. It is important to investigate the characteristic of natural gas market and the lead-lag relationship between natural gas prices and spot prices. Research on the lead-lag relationship can efficiently help investors better predict the prices and adjust investment plans to avoid risks. However, previous investigations on the lead-lag relationships between spot and futures prices are mainly focused on stock index futures, bulk commodities and energy products and there are fewer works to explore the regular of natural gas. For example, Hasbrouck [1] analyzes the standard & Poor's 100 and the NASDAQ 500 index of the day price formation. The author shows that the corresponding mini futures play

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a leading role in price discovery. Zhang [2] uses correlation analysis and Granger causality test to analyze the relationship of spot and futures in CSI 300 Index. Their result is that the correlation of spot and futures in CSI 300 Index is very strong, but they do form a mutually determined relationship.

Srinivasan and Ibrahim [3] examine Gold futures and spot markets of NCDEX by VECM and ECM–EGARCH models. The result indicates that the spot market of Gold plays a dominant role and serves as effective price discovery vehicle. Shakeel and Purankar [4] find bidirectional causality relationships between spot and futures series of castor seed and soybean, suggesting that both the spot and futures markets of the selected agricultural commodity play the leading role through price discovery process in India. Mehrara and Hamldar [5] investigate the relationships between spot and futures prices in Brent crude oil market and find that the coefficient of the ECT and lagged explanatory variables are significant in both equations which indicates that long-run as well as short-run bidirectional causalities between log of spot and futures prices. Liu et al. [6] research the characteristic electric power futures in Nordic electricity market and American PJM electricity market and the dynamic relationship between electrical futures and spot prices. The results show that the linear combination of futures price and spot price has balance convergence trends in the long-term. There is a long-term equilibrium relationship between futures price and spot price. Futures price and spot price have interaction and mutual influence, but futures price is in the dominant position.

Previous studies have neglected some of the problems. First of all, there are fewer studies exploring the causal relationships between the natural gas spot market and futures market, and as the market of natural gas becoming more and more important, the research to natural gas market is increasingly needed. Secondly, past studies for spot and futures only consider the linear Granger causality and ignore the actual nonlinear behaviors, but as shown in many researches, the nonlinear structures of energy prices have been widely considered. For example, Davis and Rodriguez-Yam [7] use the Structural Break Estimation for Nonstationary Time Series Models and Savolainen [8] use the Markov regime switching models to describe the behavior of energy futures returns on a commodity level; Bekiros et al. [9] emphasize the role of economic and firm-level uncertainty measures in predicting volatility of stock returns, and presage against using linear models which are likely to suffer from misspecification in the presence of parameter instability and nonlinear spillover effects. Therefore, this paper is based on the previous studies, using MF-DCCA method and the linear and nonlinear causality tests to examine the causal relationships between spot and futures markets for natural gas.

This paper uses the linear and nonlinear causality tests to explore the causal relationships between natural gas spot and futures prices in the New York Mercantile Exchange. The results show that the natural gas futures are the linear Granger reasons in spot price, and there are bidirectional nonlinear causality relationships between natural gas spot and futures prices. Further, it explores the reasons of nonlinear causality, and finds that the volatility spillover can partly explain the nonlinear causality between spot and futures prices.

The remainder of the paper is organized as follow. Section 2 outlines the empirical method. Section 3 explains the data and their preliminary features. Section 4 reports the empirical results and Section 5 concludes.

2. Econometric methodology

This section gives a brief description on the econometric methodology of linear and nonlinear causality tests for the causal relationships. The linear causality test is the standard Granger [10] method built on the predictive regression. The nonlinear causality test is the Diks and Panchenko [11] method, a modified version of Hiemstra and Jones [12] method.

2.1. Linear Granger causality test

For the null hypothesis that the variable X_t cannot Granger cause Y_t. The test equation of traditional linear Granger causality can be written as,

$$\Delta Y_t = \gamma + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{j=1}^{q} \beta_j \Delta X_{t-j} + \varepsilon_t \tag{1}$$

where, γ is a constant, p and q are the lag lengths and the disturbance term ε_t is assumed to be a white noise. ΔX_t and ΔY_t denote the first differences of X_t and Y_t, respectively. The null hypothesis of no Granger causality was described as the equation: $\beta_1 = \beta_2 = \cdots = \beta_q = 0$. The standard Wald F-statistic is used to detect the Granger causality relationship as,

$$F = \frac{(RSS(p) - RSS(p, q))/q}{RSS(p, q)/(T - q - p - 1)} \sim F(p, T - p - q - 1) \tag{2}$$

where, $RSS(p, q)$ is the sum of squared residuals of Eq. (1), $RSS(p)$ is the sum of squared residuals of a univariate auto-regression for ΔY_t with the lag order p, and T is the number of observations.

Engle and Granger [13] argued that, if two series are cointegrated, the causality testing should be performed based on a vector error correction (VECM) specification rather than an unrestricted VAR. The VECM has the following form:

$$\Delta Y_t = -p(Y_{t-1} - \lambda X_{t-1}) + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-1} + \sum_{j=1}^{q} \beta_i \Delta X_{t-i} \tag{3}$$

where, $[1 - \lambda]$ is the cointegration vector and λ is the cointegration coefficient.