Are Futures Prices Influenced by Spot Prices or Vice-versa? An Analysis of Crude Oil, Natural Gas and Gold Markets

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Abstract

Considering the financial theory based on cost-of-carry model, a futures contract price is always influenced by the spot price of its underlying asset, as long as the futures price is determined as the sum of the underlying asset’s spot price and its cost of carrying or storing. The aim of this paper is to verify if there are dynamic connections between spot and futures prices as stated by the cost-of-carry model, and to identify the direction of causality. The empirical analysis is conducted on three different commodity markets, namely crude oil, natural gas and gold. We estimate a battery of recursive bivariate VAR models over a sample of daily spot and futures prices ranging from January 1997 to September 2013. Using the recursive Granger-causality analysis, we show that some interactions between spot and futures prices clearly exist and they mainly depend on market type and futures contract’s maturity.

JEL Class.: G13, C32, C58

Keywords: commodity markets, spot and futures prices, recursive estimation, Granger-Causality

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1 Introduction

The price discovery role of futures contracts and the possibility they offer to reduce particular risks increase the importance of studying the futures markets and the relationship between spot and futures prices. The futures contract prices, particularly in commodity markets, transmit information to all economic agents. Producers may base their supply decisions on the futures contract prices, while physical traders might use futures contracts as a reference to price their commodities. Thus, there may be assumed that futures markets dominate spot commodity markets.

There are two main financial theories about the spot-futures prices interaction, respectively the non-arbitrage theory (cost-of-carry model) and the asset pricing theory. According to the former approach, the futures price must hold the following condition in order to avoid arbitrage opportunities:

\[ F_{t,\tau} = (1 + r_\tau)S_t - (c_{t,\tau} - k_\tau), \]  \hspace{1cm} (1)

where \( F_{t,\tau} \) denotes the futures price of a commodity at time \( t \) for delivery at \( t + \tau \), \( S_t \) is the spot price, \( r_\tau \) is the risk-free \( \tau \)-period interest rate, \( P_t \) represents the spot price at time \( t \), \( c_{t,\tau} \) is the capitalized flow of marginal convenience yield, and \( k_\tau \) denotes the per-unit cost of physical storage.

The second approach, namely the asset pricing theory, establishes a relationship between the futures price and the expected future spot price conditional on an information set \( I_t, E_t(S_{t+\tau}) \). In this case, the futures price is a biased estimate of the future spot price, and it is given by

\[ F_{t,\tau} = E_t(S_{t+\tau}) - (R_\tau - r_\tau)S_\tau, \]  \hspace{1cm} (2)

where \( R_\tau \) denotes the risk-adjusted discount rate, and \( (R_\tau - r_\tau) \) represents the risk premium.

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The common way to value a futures contract is by using the cost-of-carry model, which underlines that the futures price should depend upon the current spot price and the cost of carrying or storing the underlying good from now until the delivery. Nevertheless, even if the above equations denote an explicit relationship between spot and futures, no information about the direction of causality between these prices is offered. This lacking is covered by different studies as, for example, Bekiros and Diks (2008) or Hernandez and Torero (2010).

The aim of this paper is to verify if there are dynamic connections between spot and futures prices of crude oil, natural gas and gold commodities, as statued by the cost-of-carry model, and to identify the direction of causality. Thus, the article contributes to the existing literature by empirically investigating the direction of information flows between spot and futures through a recursive analysis in which the Granger-causality (hereafter GC) test is performed. The results have implications for producers, policymakers, hedgers and speculators.

The remainder of this paper proceeds as follows. Section 2 contains the literature review about the interactions between spot and futures prices, while section 3 is dedicated to the data description, the applied methodology and the results of our analysis. Finally, section 4 concludes.

2 Literature review

The literature examining spot and futures interactions in commodity markets is fairly extensive. Many studies provide evidence for efficient futures markets and equally large number contradicts an unbiased futures price prediction interpretation (Serletis, 1991; Bopp and Lady, 1991; Moosa and Al-Loughani, 1994).

Some of recent works are closer to our research in terms of studying a similar set of commodities (crude oil, natural gas and gold). Thus, Chinn and Coibion (2013) analyse four groups of commodities that also include crude oil, natural gas and gold. The aim of their research is to examine whether futures prices are unbiased and/or accurate predictors of subsequent prices, and results mainly show that precious metals are poor predictors of subsequent prices changes, while energy futures fair much better. They also emphasize a broad decline in the predictive content of commodity futures prices since the early 2000s. Arouri, Hammoudeh, Lahiani and Nguyen (2013) also investigate the efficiency of energy and precious metal markets, by employing four linear and non linear models. Their findings confirm that futures prices do not constitute unbiased predictors of future spot prices, although futures prices are found to be cointegrated with spot prices. Other recent works that focus on the ability of futures price to predict future changes in spot price are made by Alquist and Kilian (2010), and Alquist, Kilian and Vigfusson (2012).
2.1 Crude oil

Researches regarding the interactions between crude oil’s spot and futures prices are numerous. Many of them analyse the price of West Texas Intermediate (WTI), while others study the price of Brent and Dubai crude oil.

Studies with similar set of crude oil spot and futures prices are Bekiros and Diks (2008), Lee and Zeng (2011), Liu and Wan (2011) or Nicolau (2012). Bekiros and Diks (2008) investigate the causal linkages between daily spot and futures prices for maturities of one, two, three and four months of WTI crude oil over two periods: October 1991 - October 1999 and November 1999 - October 2007. The conventional linear GC test and a new nonparametric test for nonlinear causality after controlling for cointegration are applied. Their results show that the linear causal relationships disappear after cointegration filtering while, in some cases, causal relationships are found in both periods after using a GARCH filtering. This indicates that spot and futures returns may exhibit asymmetric GARCH effects and statistically significant higher order conditional moments. The results imply that, if nonlinear effects are accounted for, neither markets leads or lags the other consistently.

Lee and Zeng (2011) use the same time series over a period ranging from January 2, 1986 to July 6, 2009. They test causalities between spot and futures oil prices with linear, nonlinear, and quantile methods. Linear and nonlinear methods present bi-directional Granger causalities, while the quantile method shows different results. In this case, spot oil prices indeed cause futures oil prices, but the causality goes in the opposite direction only for one-month futures.

The analysis conducted by Nicolau (2012) covers the period 1999/01/01-2012/07/29. She carries out a GC test on full sample and two subsamples (before and during the actual crisis) to determine the direction of information flows between spot and futures oil markets. The paper concludes that the financial literature according to which futures prices predicts spot prices does not apply for all types of WTI futures contracts. Only futures with shorter delivery dates influence West Texas Intermediate (WTI) spot prices.

Lean, McAleer and Wong (2010) analyse the market efficiency of crude oil spot and futures, by using two approaches, respectively mean-variance (MV) and stochastic dominance (SD). This contribution uses WTI crude oil data from 1989 to 2008 and the results show no evidence of any MV and SD relationships between crude oil spot and futures indices. Thus, they prove that there is no arbitrage opportunity between crude oil spot and crude oil futures markets, spot and futures do not nominate one another, investors are indifferent to investing spot or futures, and the spot and futures crude oil markets are efficient and rational.

More recent studies regarding crude oil spot and futures prices that use GARCH models as methodology are made by Arouri, Lahiani, Lévy and

2.2 Natural gas market

The interactions between the natural gas spot and the futures prices is analysed in a less extensive number of studies, and rarely the analysis is conducted exclusively in the natural gas market.

In this field of investigation, Herbert (1993) is one of the first who examines the relationship between the spot price for natural gas for a delivery month and the futures contract price for the same delivery month by estimating a regression equation. The results provide a good summary of the relationship between spot and futures prices for the time period, and it appears that the natural gas futures market is inefficient. This is consistent with Chinn and Coibion (2013) or Arouri, Hamroudeh, Lahiani and Nguyen (2013). Later, Herbert (1995) points out several distinguishing features of the relatively new (at that time) but interesting and very volatile short-term futures and cash markets for natural gas. His results show the importance of volume of trade in influencing price volatility.

Modjtahedi and Movassagh (2005) analyse exclusively the natural gas futures, but among their results is also presented that futures prices are less than expected future spot prices, so that futures are backwardated. Buchanan, Hodges and Thesis (2001) realize an attempt to predict the direction of natural gas spot price movements using trader positions. More recent studies regarding the interactions between spot and futures natural gas markets are those of Cartea and Williams (2008) or Ederington and Salas (2008).

Other researches analyse the correlation between futures prices of natural gas and other commodities (e.g. Tonn and McCarty, 2010, for natural gas-crude oil interactions), or use natural gas futures markets data in order to develop models that could improve hedging and forecasting performance (Root and Lien, 2003; Mu, 2007; Park, Mjelde and Bessler, 2008; Kao and Wan, 2009).

2.3 Gold market

The metal markets are frequently analysed in literature, but gold market has received the most attention from academic researches. The dynamic properties of gold spot and futures prices have been investigated, among others, by Ball, Torous and Tschoegl (1985), Bertus and Stanhouse (2001) and Hammoudeh, Malik and McAleer (2011).

Gold is considered an important tool for risk hedging as well as investment avenue, therefore predicting its price has become very important to investors. A range of different and complex methods used in this respect are mentioned in literature\textsuperscript{1}.

\textsuperscript{1}Shafiee and Topal (2010), for example, present a modified econometric version of the
There are many studies regarding the relationship between macroeconomic indicators and gold price dynamics, emphasizing the correlation between inflation and gold price. Thus, Tully and Lucey (2007) investigate macroeconomic influences on gold via an asymmetric power GARCH (AP-GARCH) model. Using gold cash and futures data over a long period (1983-2003), their results confirm that the US dollar is the main, and in many cases the sole, macroeconomic variable which influences gold.

The influence of macroeconomic variables on the volatility of gold market is also met in the financial literature. Batten, Ciner and Lucey (2010), for example, model the monthly price volatilities of four precious metals (gold, silver, platinum and palladium) prices and investigates the macroeconomic determinants of these volatilities. According to their results, gold volatility is shown to be explained by monetary variables. The intensity direction and the speed of impact of US macroeconomic news announcements on the return, volatility and trading volume of gold is examined also by Elder, Miao and Ramchander (2012). Their results show that announcements regarding an unexpected improvement in the economy tend to have a negative impact on gold price, and the volatility is positively influenced by economic news.

As in the case of natural gas, gold spot and futures are frequently used in models designed to improve hedging and forecasting performance (see Chinn and Coibion, 2013; Arouri, Hammoudeh, Lahiani and Nguyen, 2013).

3 Empirical analysis

3.1 Data description

As long as, according to the non-arbitrage and asset pricing theories, the relationship between spot and futures prices explicitly exist, the aim of our work is to identify the direction of causality between spot and futures prices in three important commodity markets, respectively crude oil, natural gas and gold, by employing a recursive GC test.

We prefer commodity markets because they are more tied to current economic conditions, in contrast to more traditional financial assets. Investors, speculators, hedgers and policy makers look at the commodity markets as alternative investment instrument for hedging against risk in equity markets. Crude oil, natural gas and gold are particularly desirable asset classes for international portfolio diversification due to their different volatile returns and low correlations with stocks (Arouri and Nguyen, 2010; Daskalaki and Skiadopoulos, 2011; Hammoudeh, Araújo-Santos and Al-Hassan, 2013). At long-term trend reverting jump and deep diffusion model for forecasting natural-resource commodity price. Their study validates the model and estimates the gold price for the next 10 years, based on monthly historical data of nominal gold price. Pursuing the same goal, Zhou, Lai and Yen (2012) propose an improved empirical mode decomposition model, and their experiment results show that the proposed system has a good forecasting performance.
the same time, the financial literature has proven for decades the inflationary role of crude oil price and the feature of gold investments as hedging tool against inflation. The natural gas commodity has become an increasingly valuable resource. Due to its low environmental impact and to rapid growth in Liquefied Natural Gas (LNG) use, the consumption of natural gas is expected to increase at global level.

The available sample ranges from 1997/01/07 to 2013/09/16 ($T = 4355$), and the starting date corresponds to that from which the time series for natural gas spot price are available. All prices are expressed in US dollars. In our analysis, we use the logarithmic transformation, so that the first differences can be interpreted as market returns.

The spot prices used in the analysis are the daily London PM Fix for gold, and the closing spot prices of West Texas Intermediate (WTI) crude oil and Henry Hub natural gas. The sources for these data are the Energy Information Administration (EIA) for WTI and Henry Hub, and the Thomson Reuters Datastream for gold.

The futures prices of crude oil and natural gas are the official closing prices at 2:30 p.m. from the trading floor of the NYMEX. We use four types of time series regarding these futures contracts, denoted $F1$, $F2$, $F3$ and $F4$. $F1$ represents a futures contract specifying the earliest delivery date, while $F2$, $F3$ and $F4$ represent the successive delivery months. For crude oil, each futures contract expires on the third business day prior to the 25th calendar day of the month preceding the delivery month, while natural gas contract expires three business days prior to the first calendar day of the delivery month. The source of data for crude oil and natural gas futures contracts is the Energy Information Administration.

With regard to the gold futures price, we use the price of the nearby contract quoted on COMEX, as offered by the Thomson Reuters Datastream.

Figure 1 illustrates the available time series plots. Generally two patterns emerge. First, all three graphics reveal a strong positive correlation between spot and futures prices. More precisely, the time series appear to be cointegrated. Second, all futures markets exhibit strong contango condition during the entire sample period, especially for $F3$ and $F4$ contracts. The contango position is normal for our futures contracts due to their underlying assets: crude oil, natural gas and gold are non-perishable commodities, so they have a cost-of-carry.

The continuing decline in the crude oil prices after the mid of 2008 year reflects the decelerating economies across the globe and an attendant shump in oil demand. Although the OPEC cut its official production starting september 2008, the decline continued until the second quarter of 2009, when the prices rose moderately due to more favorable economic news (EIA - Energy Information Administration, 2008, 2009). The natural gas prices

Figure 1: Time series plots (in logarithms)

(a) Crude Oil

(b) Natural gas

(c) Gold
usually follow almost the same pattern of crude oil prices. This confirms the economic theory according to which the prices of crude oil and natural gas are related because these commodities are substitutes in consumption and also complements in production. It should be noted, however, the evolution of natural gas time series before the crisis when, for very short periods of time, both spot and futures prices reached high levels. The most important is the spike in spot price from 2003/02/25. According to the EIA reports, the high price level is due to an Arctic blast of cold, combined with strong space-heating demand and limited supply alternative\textsuperscript{3}, being well known that natural gas prices are highly sensitive to weather swings and supply disruptions (Mastrangelo, 2007).

The continuous increasing in gold price, starting the end of 2007, confirms the importance of gold as hedging tool during economic turmoil.

3.2 Methodology

In order to analyse the dynamic relationships between spot and future prices, we use a recursive GC test. Thus, possible structural breaks in the causality patterns can be detected.

In the financial literature, a common technique to assess the model stability over time is to compute parameter estimates over a rolling window of a fixed size through the sample (see, for example, Hernandez and Torero, 2010). Although, due to the large size of our available sample, we opt for the recursive estimation for the following reasons. First, with this method there is no need to choose the optimal window size.\textsuperscript{4} Second, the rolling window has always a fixed size in each estimation period, because the subsample is updated by dropping the first observation, while another observation is added at the end. This mechanism of excluding the first observations determines a loss of information. Therefore, we decide to use the recursive estimation that preserves such information by enlarging the sample size at each iteration, though the estimation performs better. We consider this method more useful to progressively account for the effects of the actual financial crisis.

In this paper we estimate a battery of bivariate VAR(\(q\)) models in which the first variable is the logarithm of the spot price (\(S_t\)) and the second is the logarithm of a futures price (\(F_t\)). Practically, we carry out 9 sequences of estimations, 4 for crude oil and natural gas commodities (spot versus F1, F2, F3 and F4, respectively), and a unique sequence spot-F1 gold. The

\textsuperscript{3}Source: http://www.eia.gov/naturalgas/weekly/archive/2003/02_27/ngupdate.asp.

\textsuperscript{4}It is well known that, in the rolling estimation, the use of different window sizes may lead to different empirical results. The determination of the optimal window size in a rolling estimation has been widely discussed in literature. See, for example, Granger and Newbold (1986), West and McCracken (1998), Pesaran and Timmermann (2007), Inoue and Rossi (2010) or Giacomini and Rossi (2012).
general setup is

$$A(L)x_t = \mu + \varepsilon_t \Rightarrow x_{i,t} = \mu_i + \tilde{x}_{i,t-1}' \beta_i + \tilde{x}_{j,t-1}' \theta_j + \varepsilon_{i,t}, \quad (3)$$

where $\mu$ is a constant, $x_t = [S_t \ F_t]'$, $i = 1 - j$ is a selection index ($i = 1, 0$) for which $S_t = x_{0,t}$ and $F_t = x_{1,t}$, the vector $\tilde{x}_{i,t-1} = [x_{i,t-1} \ldots x_{i,t-q}]'$ contains $q$ lagged variables and $\varepsilon_t$ is a bivariate white noise process. It is worth noting that the model parameters $\beta_i$ and $\theta_j$ are time-varying, since they are recursively computed; then, we carry out the recursive GC analysis and we repeat this procedure throughout the sample.

Let $T$ be the total amount of our sample observations, for $t = \tau, \tau + 1, \tau + 2, \ldots, T$, where $\tau$ represents the starting window; the recursive GC procedure applies to sample observations in the window $[1, t]$ to calculate the recursive Wald test statistic

$$W_{j,t} = \hat{\theta}_{j,t}' \hat{\Sigma}_{j,t}^{-1} \hat{\theta}_{j,t} \quad \text{with} \quad j = 0, 1, \quad (4)$$

where, at each iteration, the estimated covariance matrix of $\theta_{j,t}$ is

$$\hat{\Sigma}_{j,t} = \frac{1}{t} \sum_{k=1}^{t} \tilde{x}_{j,k} \tilde{x}_{j,k}'. \quad (5)$$

Equation (5) can be easily computed by multiplying by $(t - 2q - 1)/t$ the covariance obtained via the OLS. For each $t$, the null hypothesis is $H_0 : \theta_{j,t} = 0$.

All the estimations are computed starting from the initial window $\tau = 3005$, which corresponds to the period that goes from 1997/01/07 to 2008/07/14. The choice of the initial window period is motivated by the fact that on July 14, 2008 the financial authorities stepped into assist America’s two largest lenders, Fannie Mae and Freddie Mac, owners or guarantors of about 5 trillion worth of mortgages and home loans. We suspect that this information caused significant reactions on financial markets. Figures 1 (a) and (b), clearly show that the natural gas and crude oil spot and futures prices are rapidly declining after that date.

The whole procedure runs a series of $T - \tau + 1 = 1351$ iterations and, at each iteration, it displays the GC test statistics and the related critical values taken from the conventional $\chi^2_q$ distribution. At each estimation period the Inoue and Rossi (2005) critical values are also calculated, since it is well known that in sequential tests the conventional critical values lead to size distortions by rejecting the null hypothesis with asymptotic probability close to one. The technique proposed by Inoue and Rossi (2005) provides a simply and elegant solution to this problem. Once a confidence level $\alpha$ is given, we reject $H_0$ when the test statistic $W_{j,t}$ is greater than the critical value. In this case we conclude that the time series $x_{j,t}$ Granger-causes $x_{i,t}$. Before

\footnote{Source: \url{http://www.economist.com/node/16640249}.}
computing the test statistic in equation (4), it is necessary to specify an appropriate model at each iteration. Since in our analysis we have to carry out $T - \tau + 1$ estimations for each bivariate VAR, we need to specify a total amount of $9 \times 1351 = 12159$ models. Therefore, an automatic procedure is required.

We propose an algorithm that, for each couple $S_t-F_t$ and for all estimation periods, proceeds as follows:

1. initially, we need to test for stationarity, since the possibility of cointegration emerges from Figure 1. We use three different tests for this purpose: the standard ADF (Dickey and Fuller, 1979), the PP (Phillips and Perron, 1988), the non parametric KPSS test (Kwiatkowski, Phillips, Schmidt and Shin, 1992) and the DF-GLS test (Elliott, Rothenberg and Stock, 1996);

2. after testing for the presence of a unit root in our series, the next step is to determine the optimal lag-length ($q$). The procedure consists of minimising the Akaike (AIC), the Bayesian (BIC) and the Hannan-Quinn (HQC) information criteria for each bivariate VAR in levels. Even if, according to the Efficient Markets Theory, excess returns cannot be predicted by using strategies based on historical prices, we try to improve the statistical accuracy of our models by allowing the current prices to depend on the past information.\(^6\) Accordingly, we assume that $q_{\text{max}} = 5$ is the maximum value for lags. This value corresponds to the workweek, therefore it can be reasonable for daily financial data; on the other hand, we consider spurious all the correlations of higher order. As it is widely known, the three information criteria can return the same result or not. When they provide the same result, the corresponding lag is automatically selected; otherwise, the selection of lags is made by carrying out the Ljung and Box (1978) test residuals for autocorrelation (hereafter AC) from order 1 to order 5. The procedure is simple: for each lag a bivariate model is estimated and it is accompanied by ten values of the AC tests (5 tests for each couple of variables). The selected lag is that of the model with the minimum number of rejections. If the maximum number of rejections is obtained for two different lag specifications, the minimum lag order is selected in order to reach the maximum model parsimony;

3. since Figure 1 shows that the time series concerning the same commodity follow common trends, the optimum lag selected in the previous step is crucial for carrying out the Johansen (1991, 1996) test for cointegration. Checking for cointegration is extremely important because:

   - if the cointegration rank is $r = 0$, the spot and futures time series

\(^6\)See, for example, chapter 2 of Campbell, Lo and MacKinlay (1997) for a detailed discussion on this topic.
are two independent $I(1)$ processes (integrated of order one), thus we estimate a bivariate VAR in differences, then we carry out a standard GC analysis;

- if the cointegration rank is $r = 1$, there is cointegration between spot and futures time series, and the GC analysis is carried out by using the Toda and Yamamoto (1995) (see also Dolado and Lütkepohl, 1996) method; this technique consists of estimating an augmented bivariate VAR($q + 1$) in levels, then testing the GC simply via equation (4) by imposing $H_0: \theta_{j,t}^{(1)} = \ldots = \theta_{j,t}^{(q)} = 0$, where the superscript indicates the single element of vector $\theta_{j,t}$;

- if the cointegration rank is $r = 2$, the spot and futures time series are two $I(0)$ processes (stationary or integrated of order zero), thus we estimate a bivariate VAR in levels, then we carry out a standard GC analysis. Clearly, $r = 2$ is assumed automatically in all cases in which the unit root tests conclude in favor of stationarity.

The deterministic terms we adopt in the recursive estimation depend on the commodity: observing Figure 1 the “restricted constant” case seems to be the more appropriate for natural gas, while the “unrestricted constant” is used for crude oil.\textsuperscript{7} For the gold commodity we select the “unrestricted trend”, since the ADF test often rejects the null in presence of a quadratic trend (see Table 2) and this choice is also supported by the recursive estimation of the cointegration rank which returns $r = 2$ for almost all $t$.\textsuperscript{8}

4. finally, two GC test statistics are provided. The null hypothesis of the former test statistic is that spot does not Granger-cause futures, while the null in the latter test statistic is that futures does not Granger-cause spots. At this step, two different critical values are calculated: the first is taken from the standard $\chi^2_q$ distribution and the second, suggested by Inoue and Rossi (2005), is

$$\kappa_{q,t} = c^2_{q,\alpha} + q \ln \left( \frac{t}{T} \right),$$

where $\alpha$ is the desired significance level and $q$ is the number of restrictions imposed by $H_0$. The values of $c_{q,\alpha}$ are obtained from Table 1 of Inoue and Rossi (2005).

\textsuperscript{7}More precisely, both restricted/unrestricted constant cases have been tried and then compared for crude oil. All the preliminary estimates are available upon request from the authors.

\textsuperscript{8}In the initial iterations, the $\lambda$-max test for rejects the null $r = 2$ only 13/1351 times (0.962\%) with low $p$-values ranging from 0.5040 to 0.0962.
Table 1: ‘One shot’ estimations

Pre-crisis analysis (from 1997/01/07 to 2008/07/14, $T = 3005$ observations)

<table>
<thead>
<tr>
<th>Comm. market</th>
<th>Bivariate VAR</th>
<th>lags</th>
<th>IC</th>
<th>coint. rank</th>
<th>AC tests (reject)</th>
<th>$S_t \rightarrow F_t$ test stat.</th>
<th>$p$-val.</th>
<th>$F_t \rightarrow S_t$ test stat.</th>
<th>$p$-val.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Oil</td>
<td>spot-F1</td>
<td>1</td>
<td>BIC</td>
<td>1</td>
<td>10/10</td>
<td>13.998</td>
<td>0.0002</td>
<td>34.375</td>
<td>0.0000</td>
</tr>
<tr>
<td>Crude Oil</td>
<td>spot-F2</td>
<td>4</td>
<td>BIC</td>
<td>1</td>
<td>10/10</td>
<td>24.144</td>
<td>0.0000</td>
<td>43.480</td>
<td>0.0000</td>
</tr>
<tr>
<td>Crude Oil</td>
<td>spot-F3</td>
<td>4</td>
<td>BIC-HQC</td>
<td>1</td>
<td>10/10</td>
<td>18.152</td>
<td>0.0012</td>
<td>27.913</td>
<td>0.0000</td>
</tr>
<tr>
<td>Crude Oil</td>
<td>spot-F4</td>
<td>4</td>
<td>BIC-HQC</td>
<td>1</td>
<td>10/10</td>
<td>18.688</td>
<td>0.0009</td>
<td>19.221</td>
<td>0.0007</td>
</tr>
<tr>
<td>Nat. gas</td>
<td>spot-F1</td>
<td>4</td>
<td>BIC</td>
<td>1</td>
<td>10/10</td>
<td>3.1116</td>
<td>0.5393</td>
<td>948.68</td>
<td>0.0000</td>
</tr>
<tr>
<td>Nat. gas</td>
<td>spot-F2</td>
<td>4</td>
<td>BIC</td>
<td>1</td>
<td>10/10</td>
<td>4.5689</td>
<td>0.3345</td>
<td>814.15</td>
<td>0.0000</td>
</tr>
<tr>
<td>Nat. gas</td>
<td>spot-F3</td>
<td>4</td>
<td>BIC-HQC</td>
<td>1</td>
<td>10/10</td>
<td>6.1691</td>
<td>0.1869</td>
<td>717.61</td>
<td>0.0000</td>
</tr>
<tr>
<td>Nat. gas</td>
<td>spot-F4</td>
<td>4</td>
<td>AIC-BIC-HQC</td>
<td>1</td>
<td>10/10</td>
<td>3.1577</td>
<td>0.5318</td>
<td>654.56</td>
<td>0.0000</td>
</tr>
<tr>
<td>Gold</td>
<td>spot-F1</td>
<td>2</td>
<td>AIC-HQC</td>
<td>2</td>
<td>10/10</td>
<td>17.6450</td>
<td>0.0001</td>
<td>651.56</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Full sample analysis (from 1997/01/07 to 2013/09/16, $T = 4355$ observations)

<table>
<thead>
<tr>
<th>Comm. market</th>
<th>Bivariate VAR</th>
<th>lags</th>
<th>IC</th>
<th>coint. rank</th>
<th>AC tests (reject)</th>
<th>$S_t \rightarrow F_t$ test stat.</th>
<th>$p$-val.</th>
<th>$F_t \rightarrow S_t$ test stat.</th>
<th>$p$-val.</th>
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<tbody>
<tr>
<td>Crude Oil</td>
<td>spot-F1</td>
<td>4</td>
<td>AIC-HQC</td>
<td>1</td>
<td>10/10</td>
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<td>0.0103</td>
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<td>BIC</td>
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<td>0.4620</td>
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<td>AIC-BIC-HQC</td>
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<td>13.983</td>
<td>0.0009</td>
<td>960.40</td>
<td>0.0000</td>
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</tbody>
</table>

*Gold, Ljung-Box test for autocorrelation:*
- spot-F1, series: spot, lags: 5, test-stat.: 58.4127, p-value: 0.0000

**NOTE:** Logarithmic transformations of the variables spot and futures are used.
The null hypotheses of the GC tests are $H_0: 'S_t$ does not Granger-cause $F_t'$ and $H_0: 'F_t$ does not Granger-cause $S_t'$ respectively.
The $p$-values are those of the conventional $\chi^2$ distribution. The confidence level for each test carried out in the algorithm is $\alpha = 0.05$.
Johansen test with unrestricted constant and trend for gold.
3.3 Full sample analysis

In this section we present a preliminary analysis made by using the starting sample (the so called pre-crisis period) and the entire sample. These scenarios correspond to the first and the last iterations of the above proposed algorithm. The results are presented in Table 1.

Table 1 highlights that, in natural gas, the spot prices do not Granger-cause futures prices, but the futures contracts Granger-cause the price of their underlying assets independently of the maturity and the estimation period. So, the prices of futures contracts convey information about expectations of market participants concerning the spot prices at the maturity date.

With regard to the crude oil and gold markets, causality goes both ways when we analyze the pre-crisis period. A different pattern is met in the case of the full sample estimation, which indicates that crude oil spot price Granger-causes F3 and F4, but not vice-versa.

The results presented in Table 1 are consistent with the property according to which Granger-Causality must exist in at least one direction when two variables are cointegrated (see, among others, Miller and Russek, 1990). Moreover, the sample size is sufficiently large to overcome the problem of low power that generally affects the results provided by the Toda and Yamamoto (1995) approach. Anyway, these are preliminary results obtained via a ‘one shot’ estimation with conventional $\chi^2_q$ critical values, therefore they can suffer from some data contaminations that could lead to a misleading inference. Specifically, when the available time series are possibly affected by some outliers or breaks, the OLS method returns biased estimates. In this situation, the necessity of estimating time series parameters more robustly arises and this is the reason why we use the recursive GC analysis in the next section.

3.4 Recursive GC analysis

As we already claimed, the recursive GC analysis aims to show how the dynamic relationships between spot and futures prices vary over the sample when the number of observations augments from $\tau = 2008/07/14$ to $T = 2013/09/16$ with a one-day periodicity. Accordingly, we use the algorithm proposed in section 3.2 for $t = \tau, \tau + 1, \ldots, T$. Figures 2, 3 and 4 show the results of our analysis, and the most relevant aspect is that estimated causal relationship strictly depend on the commodity type. The values of the recursive GC are plotted in bold, the black line indicates the $\chi^2_q$ critical values, and the grey line corresponds to the Inoue and Rossi (2005) critical values $\kappa_{q,t}$ calculated according to equation (6).

In crude oil market the direction of causality is from spot to futures, excepting the couple spot-F1 that presents some particularities. The first is that F1 clearly Granger-causes spot, while the direction of causality from
Figure 2: Oil

Figure 2: Oil

NOTE: 
- test statistic $\chi^2$
- $\chi^2$ quantile
- $\kappa_{q,t}$ quantile (see Inoue and Rossi, 2005).
spot to F1 depends on what critical values we consider. According to the chi-squared distribution critical values, spot Granger-causes F1, too; so, the causality is bi-directional. If, instead, we consider the Inoue and Rossi (2005) critical values $\kappa_{q,t}$, there is no influence from spot to futures and the direction of causality goes only from F1 to spot. As we stressed in section 3.2, in recursive analysis the use of such quantiles is more appropriate than the use of standard $\chi^2_q$. Accordingly, we conclude that spot does not Granger-cause F1. The second particularity shown by Figure 2 is that the sequences of recursive GC analysis for the crude oil market evidences instability at the beginning of the analysed period. This issue does not depend on the estimation method we employed, but it is caused by the economic environment. On the one hand, the instability in financial markets played a key role. The announcement regarding Fennie Mae and Fredie Mac on 14th of July 2008 led to the immediate reactions of speculators. On the other hand, oil price is subject of external influences such as economic growth, OPEC behavior, geo-political events and hurricanes. According to the EIA the WTI crude oil price was quite unsettled during July 2008, registering both a new record high and the largest one-month decline in several years. The declines were primarily driven by demand and supply issues due to the previous very high prices that affected the consumption of oil products. The economic recovery, although anemic, has driven to stability from 2010 onwards, as also seen in Figure 2.

Focussing on the natural gas commodity (see Figure 3), the futures prices always Granger-cause the spot. From the statistical perspective, the cointegration rank is $r = 1$ and the model lag order is constant ($q = 4$). Only for the couple spot-F1 the lag order augments from 4 to 5. In this case the actual crisis does not seems not to produce significative effects on the causal relationships that remain stable over time. Neverheless, this model could suffer from some misspecification due to several rejections in the 5th-order Ljung and Box (1978) test for the spot time series.

The results of the ‘one shot’ GC tests for the gold commodity are confirmed during the entire sequence of estimations. Figure 4 clearly reveals that, with a size of $\alpha = 0.05$, the direction of causality goes from futures to spot independently of the critical value we use. Moreover, the statistical features of the recursive VAR models remain unchanged over the estimation periods. Specifically, the lag order is always $q = 2$, as jointly suggested by the AIC, HQC and sometimes by BIC; as we claimed before, the cointegration rank is $r = 2$ and the deterministic term “unrestricted trend” is used and this indicates that the time series are stationary around a quadratic trend. Finally, the high number of estimation periods in which the Ljung and Box (1978) tests for autocorrelation accept the null highlights that the recursively estimated models do not suffer of any relevant misspecification.
Figure 3: Gas

NOTE: 

test statistic  

χ² quantile  

κq,t quantile (see Inoue and Rossi, 2005).
Figure 4: Gold

spot → F1 F1 → spot

NOTE: test statistic \( \chi^2 \) quantile \( \kappa_{q,t} \) quantile (see Inoue and Rossi, 2005).

<table>
<thead>
<tr>
<th></th>
<th>tests with constant</th>
<th>tests with constant and trend</th>
<th>test with constant, trend, quadratic trend</th>
</tr>
</thead>
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<td>ADF 1298 (96.08%) PP 1351 KPSS 1351 DFGLS 1351</td>
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<td>spot</td>
<td>1351</td>
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<tr>
<td>F1</td>
<td>1351</td>
<td>1351</td>
<td>1351</td>
</tr>
<tr>
<td>F2</td>
<td>1351</td>
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</tr>
<tr>
<td>F3</td>
<td>1351</td>
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</tr>
<tr>
<td>F4</td>
<td>1351</td>
<td>1351</td>
<td>1351</td>
</tr>
<tr>
<td>Nat. gas</td>
<td>ADF 1351 PP 1351 KPSS 1351 DFGLS 1351</td>
<td>ADF 1073 (79.42%) PP 1351 KPSS 1351 DFGLS 1351</td>
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<tr>
<td>F1</td>
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<tr>
<td>F4</td>
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</tr>
<tr>
<td>Gold</td>
<td>ADF 1351 PP 1351 KPSS 1351 DFGLS 1351</td>
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</tr>
<tr>
<td>F1</td>
<td>1351</td>
<td>1351</td>
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</tbody>
</table>

NOTE: The values in this table indicate the total amount of the acceptances of \( H_0 \) for each unit root test. Only in the case of the KPSS the numbers indicate the amount of rejections. When these numbers are less than \( T - \tau + 1 = 1351 \), a subscript in parentheses is inserted, indicating the corresponding percentage. The confidence level is set to \( \alpha = 0.05 \).
4 Concluding remarks

The lower diversification benefits from equity investments during financial crises, justifies the interest of investors, hedgers and speculators in considering spot and futures commodity markets as alternative investment instruments for hedging against risk in equity markets.

In this paper we aim to analyse the causal relationships between spot and futures prices in commodity markets. To do so, we propose a battery of recursive GC analysis between spot and futures prices of the gold, natural gas and crude oil commodities over a sample which ranges from January 7, 1997 to September 16, 2013. The first estimation period, or pre-crisis period, consists of all the sample observations until July 14, 2008, the day in which the collapse of Fannie Mae and Freddie Mac was announced. The recursive analysis starts from this event onwards, so that the effects produced by the actual crisis are taken into account.

The main result of our approach is that interactions between spot and futures prices substantially depend on commodity market. In practice, we do not find an univocal direction in causality that might be universally valid, because each commodity market and each couple spot-futures we examined present its own peculiarities.

We estimate recursively a battery of bivariate VAR models, and we try to minimise the probability of having mispecified models by proposing an algorithm that, in all estimation periods, determines the more appropriate lag order and the cointegration rank before carrying out the GC tests. Spot and future prices are always cointegrated and this is not surprising. Gold represents the only exception: for this commodity we found that spot and futures time series are trend stationary, therefore the cointegration does not work. However, all the statistical features such as the number of the optimal lags or the results of the GC and autocorrelation tests do not vary significantly over time, especially when the sample is sufficiently large. Conversely, for the oil commodity, a sort of instability is visible only in the initial estimation periods. This is consistent to the uncertainty of financial markets and economic environment during the period between July 2008 and November 2009.

The results offered by our approach in crude oil market show that the market participants are not anymore indifferent in investing spot or futures. Despite the very high co-movement between natural gas and crude oil prices, the direction of causality between spot and futures in these markets is opposite. Our results show that crude oil spot price generally Granger-causes the futures oil prices, except the couple spot-futures 1-month, while futures natural gas prices Granger-cause the natural gas spot price independently of contract maturity. On the other hand, previous studies regarding the predictive content of futures contract for one commodity emphasizes that the natural gas futures have the ability to predict subsequent prices, while oil does it relatively worst (Chinn and Coibion, 2013).
Since the start of economic downturn, Bernanke (2008) noted the poor record of commodity futures markets in forecasting the course of price rises. Therefore, analyzing the directionality between spot and futures prices in order to understand if the information offered by commodity futures markets are still useful for policymakers is more important than ever. Accordingly, adding some exogenous regressors (for example, daily economic variables or specific dummy variables) could improve our approach. An analysis on the dynamics of spot and futures daily returns taking into account changes in volatility would be also useful. These topics represent fields of investigation for our further research.

References


Bernanke B.S. (2008), “Outstanding Issues in the Analysis of Inflation”, Federal Reserve Bank of Boston’s 53rd Annual Economic Con-


