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# Study of the Dynamic Relationship of Transmission Between Spot and Forward Prices in the Oil Market

**El Bouazizi Said[1], El Bouzidi Hasna[2]**

[1]LIRO, National School of Business and Management, Chouaib Doukkali University

[2]L-QUALIMAT, FSJES of Marrakech, Cadi Ayyad University

**ABSTRACT:** This paper examines the short- and long-term dynamic relationship between spot and forward oil prices. We highlight the finding that producers are bound by forward contracts for future deliveries of oil with forward prices which deprives them of any immediate increase in production and therefore have an effect on spot prices. We will process daily spot and futures prices data during the period from January 20, 2017 to December 13, 2021.The results of the causality test indicate that the relationship between spot and futures prices is bidirectional, which means that the causality is mutual. Indeed, in the short term, spot prices caused futures prices and vice versa in the medium and long term. In addition, spot oil prices have been affected by changes in the spot price at a minimal level. A spot price shock has an insignificant negative impact on oil futures prices while the impulse response of pot prices to a futures price shock was positive. Finally, we will find that the impact of extreme volatility in futures prices, when they reach their lowest level in history on April 20, 2020, on spot prices was insignificant. The results of this research contribute to the oil decision-making process.

**KEYWORDS:** Oil market, Forward price, futures prices, Panel cointegration, Variance decomposition.

## I. INTRODUCTION

The study of crude oil price dynamics has received much attention in the economics literature over the years. Often the distinction between positive and negative oil shocks is important. Indeed, in recent years, the frequency of positive and negative sequences has been striking in its magnitude, with fears that higher oil prices would lead to high inflation and lower global production. The impact on economic management of oil price fluctuations can be reduced by using the instruments provided by the market finance literature available such as futures markets. In a recent paper, Chang and Lee (2015), examine whether or not oil spot and futures prices move together over time. The motivation for this is twofold. On the one hand, it is important to understand the underlying mechanisms of price discovery in the oil spot and futures markets. On the other hand, there is an interest in studying the efficiency of the oil market, in the sense that market participants use all available information to set forward prices. Analyzing the relationship between prices over different time horizons not only allows us to analyze the impact on economic performance, but also how fluctuations could affect crucial variables in companies. The current and future price of oil is one of the most important factors in macroeconomics because in a period of shock all other prices are impacted and at all levels (Bailey W, Chan KC. 1993). The fluctuations, in all directions, of the oil price these last for various reasons, has renewed the interest in the question of what determines the spot and futures price of crude oil and has emphasized the importance of being able to predict as accurately as possible the evolution of the spot price of oil (Greenspan, 2004a,b,2005; Bernanke, 2004, 2006; Gramlich, 2004; Davies, 2007; Kohn, 2007).

In relation to previous studies, Our study is complementary and sheds light on the relationship between spot and future prices. Current prices are impacted by future decisions, and operators tend to make intertemporal choices in order to take advantage of a favorable current situation or to manage a crisis. we analyze both the short- and long-term relationship, as well as the impact of the short term on the long term and vice versa.

In this paper, we use the information provided by a theoretical model of the market for spot and futures prices of crude oil in conjunction with an empirical analysis to shed light on the existing relationship between its prices. In other words, this paper is interested in examining the current state of prices and the expectations conveyed of future oil prices via futures contracts. Specifically, this paper analyzes the short- and long-term dynamic relationship between crude oil prices over different time horizons: spot, one month, two and three months. Why is it important to know the short- and long-term relationship between spot and futures market prices? This is a vital question because changes in futures prices can have some effect on short-term spot crude oil prices. Furthermore, given that the volatility and degree of co-movements between spot and futures oil prices are identified, it seems important to obtain information about the relationships between them through generalized impulse response functions. The rest of the paper is organized in two sections. The second section contextualizes the literature review used and the research hypotheses. The third section presents the methodology adopted and the results obtained.

**2. LITERATURE REVIEW**

Several studies address the relationship between spot and futures prices. The analytical results of one study in the Chinese context revealed that the power of futures prices in setting spot oil prices in the Chinese Shanghai market is very limited compared to the international benchmark oil price from the US market. On the other hand, the Shanghai futures market has started to have an increasingly significant influence on the price transmission of the Asian oil market and better reflects the supply and demand of oil. The Shanghai market is an effective hedging tool for oil importers and refineries. Therefore, although the Shanghai crude oil futures market is still in its initial development stage, it provides an important foundation to become a regional benchmark in Asia and a useful tool for energy market players, influencing the Chinese oil industry in terms of import prices and consumption (Qi Zhang, Peng Di, , Arash Farnoosh 2021).

Using a two-country, multi-period general equilibrium model, the gap between spot and forward prices was investigated. It was shown that increased uncertainty about future oil supply shortages under plausible assumptions leads to a decrease in the spread between these prices. The increase in uncertainty also leads to an increase in the spread between these prices.

The relationship between the spot price and oil futures prices allows us to establish a forecasting relationship. Oil market participants consider that futures prices incorporate all available information and therefore represent a better forecast of the spot price. Governing institutions such as central banks and the International Monetary Fund commonly use the oil futures price as an indicator of market expectations of the spot price (Baumeister and Kilian, 2012; Svensson, 2005; IMF, 2011). To this end, several authors have investigated the question of whether futures contracts can be considered a good forecast of the spot price (Pyung and all 2022). Moosa and Al-Loughani (1994) find that futures prices are not unbiased or efficient forecasts of spot prices. Gülen (1998) believes that the posted spot price provides predictive information only in the short term, and that forward prices are efficient forecasts of the spot price. Abosedra and Baghestani (2004) have studied crude oil futures prices for durations of up to one year and conclude that futures prices are unbiased forecasts of spot prices for all maturities studied, but that only one-month and 12-month contracts outperform the naive forecast (i.e. the no-change forecast). Knetsch (2007) questions the use of futures prices as predictors and fi Pyung Kun Chu , Kristian Hoff , Peter Molnar, Magnus Olsvik (2021) studied the predictability of Brent crude oil prices. They confirmed that the simple no-change forecast works better than forecasts based on forward prices of less than one year. On the other hand, forecasts based on forward prices outperform no-change forecasts over long-term horizons of one to five years. They demonstrated the usefulness of the information reflected in long-term forward prices for forecasting long-term oil prices. Whereas it would be difficult for decision-makers to take advantage of short-term forward prices.

Hachmi Ben Ameur - Zied Ftiti - Waël Louhichi (2021) examined the relationship between spot and futures markets for a sample of commodity markets, in particular metals markets (aluminum, gold and copper), energy markets (Brent and natural gas) and agricultural markets (wheat). They revealed a bidirectional relationship between the spot and futures markets in the long term and short term, with the futures market leading the way. Changes in commodity prices first appear on the futures market, as informed investors and speculators prefer to trade on this market, which is characterized by low costs and high leverage. The information is then transmitted to the spot market through the activity of arbitrageurs, which explains the non-linearity of the relationship.

Jeonghoe Lee, Bingjiang Xia (2024) analyzed the dynamics between spot and future oil prices of different maturities. They used deep learning approaches for forecasting based on futures markets. These learning approaches are This Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), and Temporal Convolutional Neural Network (TCN), to forecast crude oil spot prices. Their research investigates the performance of these machine learning models when exploring the relationship between crude oil futures and spot prices. To contribute to the enhancement of the field of explainable artificial intelligence (xia), these two authors have incorporated extensive hyper-parameter tuning to improve the interpretability of machine learning models for forecasting using futures prices. The results of the research showed the predictive power in terms of XAI between spot and forward prices with different maturities and machine learning algorithms.

**3. METHODOLOGY AND EMPIRICAL RESULTS:**

To explore the relationship between spot and futures prices, we use data involving West Texas Intermediate (WTI) spot oil prices and Chicago Mercantile Exchange (CME) one, two, and three month futures prices over the period 20/20/2017 to 12/13/2021. We represent the VAR model:

$$S_t = \beta_1 S_{t-1} + .. + \beta_p S_{t-p} + \alpha F_T + \varepsilon_T$$

- St : Daily spot price
- Ft : Daily futures price

**3.1. Unit Root Tests:**

The unit root was determined using Levin, Lin, and Chu (2002), Im, Persarn, and Shin (2003) and other panel stationarity tests. According to the results in Table 1 both variables are non-stationary, in level, that is, there is a unit root. The first difference is used to stationaryize the time series. The six unit root tests in panel show that they are now stationary.

**Table 1. Unit root tests:**

| | ADF[a] | LLC [a] | PP [a] | Breitung [a] | IPS[a] | Hadri[b] |
|---|---|---|---|---|---|---|
| Variable (level) | | | | | | |
| $S_t$ | 4.43249 (0.6184) | 0.50389 (0.6928) | 5.19841 (0.5186) | -0.66149 (0.2541) | -0.22465 (0.4111) | 13.9644*** (0.0000) |
| $F_t$ | 1.48228 (0.9607) | 1.17384 (0.8798) | 3.12259 (0.7933) | -0.38148 (0.3514) | 1.10494 (0.8654) | 13.9839 (0.0000) |
| Variable (first difference) | | | | | | |
| $S_t$ | 444.457*** (0.0000) | -29.2633*** (0.0000) | 790.172 (0.0000) | -23.0974*** (0.0000) | -27.8106*** (0.0000) | 0.84372 (0.1994) |
| $F_t$ | 492.508*** (0.0000) | -25.7359*** (0.0000) | 164.712*** (0.0000) | -25.9331*** (0.0000) | -29.5495*** (0.0000) | -0.94980*** (0.0000) |
| Note :<br>a: The null hypothesis: the existence of the unit root (non-stationarity).<br>b: The null hypothesis: the non-existence of the unit root (stationarity).<br>The p-values are given in parentheses. *** indicate statistical significance at 1%. | | | | | | |

**3.2. Panel cointegration test:**

After taking the first differences, the series are stationary. The tests reveal evidence of panel cointegration. Using the Pedroni residual and Johansen Fisher panel cointegration tests on panel data and a Johansen VAR-based cointegration test for time series data, it appears that there is a long-run relationship between spot and forward prices. We note that time series data may contain a unit root and give a spurious regression estimation result according to Engle and Granger (1987).

The Pedroni test in Table 2 shows that out of seven different tests: PP statistics of the ρ group, panel, and group cannot reject the null hypothesis of no cointegration. Furthermore, Table 3 shows, using the Johansen Fisher test, that there is a vector relationship of cointegration since the null hypothesis of no cointegration is rejected. Therefore, the result confirms hypothesis 1 that there is a cointegrating relationship between the variables.

**Table 2. Pedroni cointegration test:**

| **Pedroni Residual Cointegration Test**<br>**Series: S F**<br>**Null Hypothesis: No cointegration** | | | | |
|---|---|---|---|---|
| | **With constant** | | **With constant and trend** | |
| | Statistic | Prob. | Statistic | Prob. |
| **Panel v-Statistic** | 18.19739 | 0.0000 | 13.92741 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| **Panel rho-Statistic** | -119.5956 | 0.0000 | -120.0061 | 0.0000 |
| **Panel PP-Statistic** | -22.71506 | 0.0000 | -27.89305 | 0.0000 |
| **Panel ADF-Statistic** | -8.283988 | 0.0000 | -9.596780 | 0.0000 |
| **Alternative hypothesis: individual AR coefs. (between-dimension)** | | | | |
| | Statistic | Prob. | Statistic | Prob. |
| **Group rho-Statistic** | -81.39563 | 0.0000 | -75.09107 | 0.0000 |
| **Group PP-Statistic** | -14.93178 | 0.0000 | -16.66543 | 0.0000 |
| **Group ADF-Statistic** | -6.790796 | 0.0000 | -7.240474 | 0.0000 |
| Note:<br>a. The null hypothesis is the absence of cointegration between the variables.<br>b. Abbreviations: ADF (Augmented Dickey Fuller); PP (Phillips Perron). | | | | |

**Table 3. Johansen Fisher Panel cointegration test:**

| **Hypothesized** | **Fisher Stat.*** | | **Fisher Stat.*** | |
|---|---|---|---|---|
| **No. of CE(s)** | (from trace test) | Prob. | (from max-eigen test) | Prob. |
| **r=0** | 39.69 | 0.0000 | 44.09 | 0.0000 |
| **r = 1** | 13.52 | 0.0354 | 13.52 | 0.0354 |
| Note:<br>a. r denotes the maximum number of cointegrating vectors.<br>b. ** and * denote statistical significance at the 1, 5% level, respectively. | | | | |

**3.3. Vector Autoregressive Model :**

The vector autoregressive (VAR) model generalizes the univariate autoregressive model to the multivariate case. This offers advantageous features such as the estimation of the dynamic interrelationship between the variables and the indifference as to the choice of the dependent variable. Furthermore, as the crude oil futures price reached its lowest level in history (-37.63$ per barrel) on April 20, 2020, this extreme price volatility is taken into account in this study by adding a dummy variable "Dummy" to examine its impact. Thus, the price volatility shock variable is worth 1 if the period coincides with this date and 0 otherwise. Table 4 presents the results of the VAR estimations and the model test diagnostics. All variables, except for a dummy variable in the spot oil price equation, are significant at the 1% level. As such, extreme volatility in futures prices does not affect spot crude oil prices.

**Table 4. Estimation of the VAR model**

| Vector Autoregression Estimates | S | F |
|---|---|---|
| S(-1) | 0.951080*** | 0.237583*** |
| | (0.01182) | (0.01543) |
| | [ 80.4691] | [ 15.4018] |
| F(-1) | 0.046519*** | 0.734285*** |
| | (0.01214) | (0.01585) |
| | [ 3.83065] | [ 46.3287] |
| C | 0.391748*** | 0.462557*** |
| | (0.17159) | (0.22394) |
| | [ 2.28309] | [ 2.06550] |
| DUMMY | -2.377986 | -58.17929*** |
| | (1.26907) | (1.65632) |
| | [-1.87380] | [-35.1257] |

| | | |
|---|---|---|
| R-squared | 0.990509 | 0.982974 |
| Adj. R-squared | 0.990487 | 0.982933 |
| F-statistic | 44251.74 | 24478.40 |
| Log likelihood | -2106.327 | -2446.141 |
| Akaike AIC | 3.307723 | 3.840346 |
| Schwarz SC | 3.323872 | 3.856495 |
| Akaike information criterion | | 6.623119 |
| Schwarz criterion | | 6.655416 |

Note: t-statistics between [ ], *** indicate statistical significance at the 1% level.

The coefficient of determination R-squared is about 0.99 for the first and 0.98 for the second equation, indicating that the selected variables explain most of the variation. For the lag structure of the VAR system, an optimal lag specification and number of lags in the VAR model are determined by minimizing the Akaike and Schwarz information criteria. Given the Akaike information criterion (AIC) of 6.62, the AIC for the spot and futures crude oil price equations are 3.31 and 3.84, respectively. Under the Schwarz criterion (SC) of 6.65, the spot and futures crude oil price equations reveal an SC is 3.32 and 3.86, respectively.

### 3.4. Granger causality test:

We emphasize that the Granger causality test can only be applied to pairs of variables and can produce spurious results when a relationship involves three or more variables. According to Granger's (1969) approach, Granger's concept of causality does not indicate a causal relationship, but rather is based solely on "predictability" or "predictive ability." According to the results in Table 5, the causal link between spot prices and futures prices is bidirectional at the 1% significance level.

**Table 5. Pawise Granger causality test**

Pairwise Granger Causality Tests

Sample: 1/20/2017 12/13/2021
Lags: 30

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| F does not Granger Cause S | 3741 | 3.32475 | 3.E-09 |
| S does not Granger Cause F | | 11.3191 | 2.E-51 |

### 3.5. Variance decomposition:

Table 6 presents the results of the variance decomposition. The numbers reported indicate the percentage of the forecast error in each variable that can be attributed to innovations in other variables (short term to long term).

The column (S shock (1) S) shows that in the first period, 100% of the changes in spot prices are explained by its own innovations. In the 10th period, over a longer period, spot price variations are still mainly due to their own variations (98.721%) while this percentage is, approximately, 99% during the first periods. This also confirms that short-term shocks have a long-term effect on the spot price of crude oil. As shown in column (S Shock (2) F), in general, oil futures prices are affected by changes in spot prices at a very minimal level.

**Table 6. The variance decomposition**

| Variance Decomposition of S: | (1)<br>S Shock (1) | S Shock (2) |
|---|---|---|
| Period | S | F |
| 1 | 100.0000 | 0.000000 |

| | | |
|---|---|---|
| 2 | 99.94898 | 0.051020 |
| 3 | 99.84889 | 0.151111 |
| 4 | 99.71599 | 0.284009 |
| 5 | 99.56239 | 0.437613 |
| 6 | 99.39698 | 0.603021 |
| 7 | 99.22623 | 0.773769 |
| 8 | 99.05477 | 0.945229 |
| 9 | 98.88584 | 1.114157 |
| 10 | 98.72166 | 1.278343 |

| | F Shock (1) | F Shock (2) |
|---|---|---|
| Period | S | F |
| 1 | 44.85050 | 55.14950 |
| 2 | 47.60764 | 52.39236 |
| 3 | 50.20254 | 49.79746 |
| 4 | 52.62955 | 47.37045 |
| 5 | 54.88849 | 45.11151 |
| 6 | 56.98330 | 43.01670 |
| 7 | 58.92084 | 41.07916 |
| 8 | 60.70986 | 39.29014 |
| 9 | 62.36017 | 37.63983 |
| 10 | 63.88202 | 36.11798 |

Indeed, in the second period, 0.051% of the variability in oil futures prices is explained by the spot price shock. At the end of the 10th period only 1.27% of the variability of forward prices can be explained by the spot price shock. In the short and long run, spot price shocks do not have a significant impact on crude oil futures price changes. This is consistent with the view that the link between spot rates to the forward price of oil is generally weak.

Column (F shock (1)) reveals that during the first period 44.85% of the variability in spot prices is attributed to changes in futures prices. This one is 63% during the 10th observation. Column (F shock (2)) indicates that at the beginning of period 1, 55% of the variability of futures prices is explained by its own innovations and this rate decreases as time goes on, it is 36% at the end of the 10th observation. We will confirm the result that the oil futures price in the current period is closely related to the futures prices in the pricing decisions.

**3.6. Impulse responses:**

An alternative method of obtaining information about the relationships between the variables is to analyze impulse response functions. These analyze the time profile of the effects of shocks on the future behavior of oil prices. Figures 1 and 2 present the impulse response to changes in spot oil prices and changes in the futures price of a standard deviation shock to spot and futures oil prices.

The DS and DF series are the first difference of spot and futures prices of crude oil, respectively. Figure 1 shows the response of futures prices to the spot price shock. The spot price shock has a significant negative impact on crude oil futures prices. The graph also reveals that the response of crude oil futures prices to spot price shocks starts to decrease from the second period.

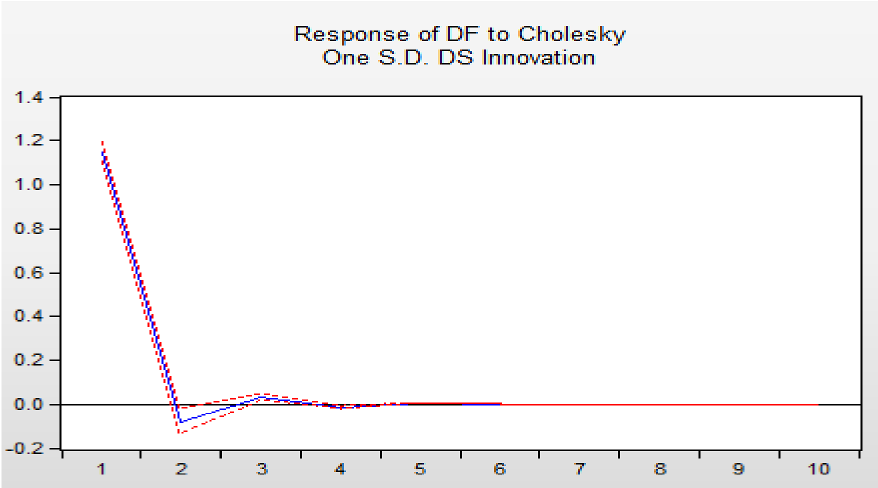


**Figure 1. Impulse response (spot prices over futures prices)**

Figure 2 shows the impulse response of the spot oil price variable to the crude oil futures price shock. A shock has a positive effect on spot prices in the first two periods, then we observe a negative effect in the third period and a positive effect thereafter; however, it is not significant.

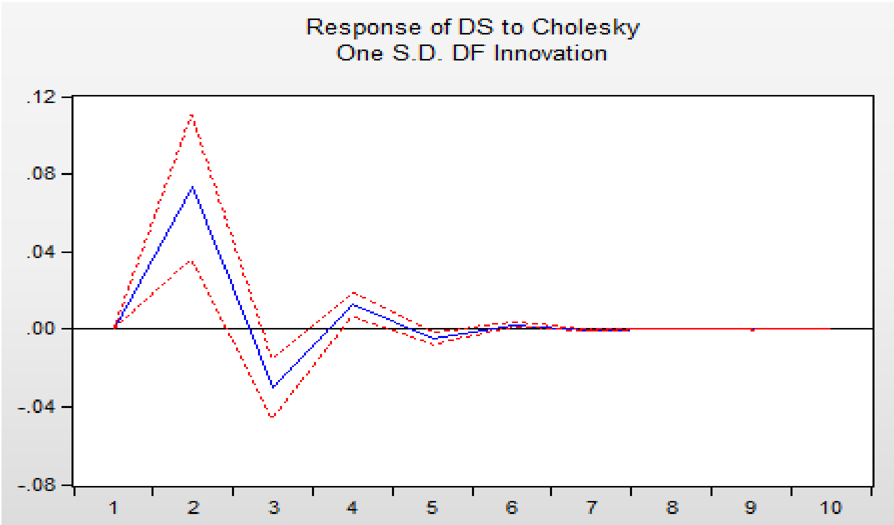


**Figure 2. Impulse response (Futures prices over spot prices)**

**4. CONCLUSION**

This paper has empirically examined the dynamic behavior of one-, two- and three-month spot and futures prices. Using the Granger causality test, variance decomposition and impulse response function analysis. It was shown that in the short run spot prices caused futures prices while in the long run futures prices caused spot prices. Since crude oil futures price movements in the short run always follow spot price movements, while spot price movements always follow crude oil futures price movements in the long run. This should capture the attention of investors, money managers and hedgers. It is essential to use this knowledge to adjust their portfolios, as spot price changes have some effect on short-term crude oil futures prices. For diversification purposes, the investment portfolio should involve crude oil and commodities that are in the opposite direction. In light of these results, a deeper understanding of the impulse response analysis reveals an intuitive impact of futures prices on spot crude oil prices. Another implication is based on the variance decomposition analysis and establishes that spot price changes are explained by its own information.

While in that a forward price shock has only a limited part of the variation in forward prices. This confirms that the futures price is closely linked to future pricing decisions. Futures markets are now an inescapable factor and investors reason in a broader intertemporal framework. The results of this research contribute to the oil decision-making process.

Our study will enable operators to better manage the volatility of spot oil prices, and public authorities to better regulate this market. Understanding the relationship also enables public operators to better manage prices. The intertemporal aspect plays a role in entering and exiting the market. The limitations of this research are that we have data over a fairly wide time horizon, and we have considered prices in the normal state of the market. We propose that researchers refine and use alternative methods of analysis that address high-frequency data, and methods that take into account the extreme values of the spot and futures market and its impact on volatility in both markets.

**REFERENCES:**


1) Abosedra, S., Baghestani, H.(2004). On the predictive accuracy of crude oil futures prices. Energy Policy 32 (12), 1389–1393.
2) Alquist, R., & Kilian, L. (2010). What do we learn from the price of crude oil futures? Journal of Applied Econometrics, 25(4) : 539–573.
3) Bailey, W., Chan KC. (1993). Macroeconomic influences and the variability of the commodity futures basis. Journal of Finance, 48: 555–573.
4) Baumeister, C., Kilian, L. (2012). Real-time forecasts of the real price of oil. J. Bus. Econ. Stat. 30 (2), 326–336.
5) Bernanke, BS. (2004). Oil and the economy. Speech presented at Darton College, Albany, GA.
6) Bernanke, BS. (2006). Energy and the economy: remarks before the Economic Club of Chicago, IL.
7) Chang, CP., Lee CC.(2015). Do oil spot and futures prices move together?. Energy Economics, 50 : 379-390.
8) Chen KC, Chen S, Wu L.(2009). Price causal relations between China and the world oil markets. Global Finance.
9) Chen, PF., Lee, CC., Zeng, JH.(2014) The relationship between spot and futures oil prices: do structural breaks matter? Energy Economics, 206-217.
10) Davies, P. (2007). What's the value of an energy economist? Presentation at the 30th Annual Conference the International Association for Energy Economics, Wellington, New Zealand.
11) Engle, R. F. & Granger, C. W. J. (1987). Co-integration and error correction: Representation,
12) Estimation, and Testing. Econometrica, 55 : 251-276.
13) Gramlich, EM.(2004). Oil shocks and monetary policy. Annual economic Kansas City, Kansas.
14) Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross- Spectral Methods. Econometrica, 37(3) : 424-438.
15) Greenspan, A. (2005). Energy, Remarks before the Japan Business Federation, Tokyo, Japan.
16) Greenspan, A. (2004a). Energy, Remarks by Chairman Alan Greenspan Before the Center for Strategic and International Studies, Washington, DC.
17) Greenspan, A. (2004b). Oil, Speech presented at the National Italian American Foundation, Washington, DC.
18) Gülen, S.G.(1998). Efficiency in the crude oil futures market. J. Energy Finance Dev. 3 (1), 13–21.
19) Hachmi, B A., Ftiti,Z., Louhichi, W. (2022). "Revisiting the relationship between spot and futures markets: evidence from commodity markets and NARDL framework," Annals of Operations Research, Springer, vol. 313(1): 171-189
20) Holmes, MJ., Otero., J.(2019), Re-examining the movements of crude oil spot and futures prices over time. Energy Economics, 82 : 224-236.
21) Im, K. S., Pesaran, M. H. & Shin, Y. (2003). Testing for Unit Roots in Heterogeneous Panels. Journal of Econometrics, 115(1) : 53-74.
22) IMF. (2011). World Economic Outlook, April 2011, Technical Report. International Monetary Fund.
23) Jeonghoe, L., Bingjiang, Xi. (2024). Analyzing the dynamics between crude oil spot prices and futures prices by maturity terms: Deep learning approaches to futures-based forecasting. Results in Engineering, 24: 103086,
24) Jones, C. M., & Kaul, G. (1996). Oil and stock markets. Journal of Finance, 51(2) : 463-491.
25) Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review, 99: 1053–1069.
26) Kilian, L. (2008a). The economic effects of energy price shocks. Journal of Economic Literature, 46: 871–919.
27) Kilian, L. (2008b). Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy? Review of Economics and Statistics, 90: 216–224.
28) Kohn, DL. (2007). The economic outlook: remarks at the Atlanta Rotary Club, Atlanta, GA.
29) Li, R., Leung, GCK.(2011). The integration of China into the world crude oil market since (1998). Energy Policy, 39(9) : 5159-5166.
30) Knetsch, T.A., 2007. Forecasting the price of crude oil via convenience yield predictions. J. Forecast. 26 (7), 527–549.
31) Moosa, I.A., Al-Loughani, N.E.(1994). Unbiasedness and time varying risk premia in the crude oil futures market. Energy Econ. 16 (2), 99–105.

32) Pyung, K.C., Hoff, k., Molnár,P., Olsvik, M.(2022). Crude oil: Does the futures price predict the spot price?. Research in International Business and Finance. 60.
33) Sanders, D.R., Manfredo, M.R., Boris, K. (2009). Evaluating information in multiple horizon forecasts: The doe's energy price forecasts. Energy Econ. 31 (2), 189–196.
34) Svensson, L.E., 2005. Oil Prices and ECB Monetary Policy. Princeton University, CEPR, and NBER.
35) Zhang, Q., Di, P., & Farnoosh, A. (2021). Study on the impacts of Shanghai crude oil futures on global oil market and oil industry based on VECM and DAG models. Energy, 223,120050.