Preliminary Research on Correlation of Gold, Crude Oil and the Dow Jones Industrial Average

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Abstract: The recent instability in the world's financial markets, especially for such a "The first energy of the world" prices for crude oil change amplitude is too large. In this paper, a preliminary discussion of gold, crude oil and the Dow Jones industrial average correlation, using a vector autoregression method to establish the VAR model, and carry on the empirical analysis. Selects the Grander causality test methods for preliminary data processing and analysis, and through the established VAR model analysis results for gold, crude oil, and carries on the preliminary discussion, the correlation of the Dow Jones industrial average fuzzy estimate their relevance. Through the correlation between long-term and short-term prediction, can find the relationship between the three products, is only the DJIA to NLSCO short-term one-way leading relationship. DJIA can lead NLSCO price, and CG price can guide the DJIA.
Keywords: VAR, Cointegration, Grander causality test, contagion effect.

INTRODUCTION

Because of the large amount of the output of crude oil in the country increased amount of crude oil, the international crude oil market share for the start of the war, crude oil prices falling, since the middle of 2014. As of January 2016, the lowest price of crude oil nears close to $26 a barrel. This is a third of the average price of crude oil, followed by the end of 2015 and early 2015's the "Thousand Shares Drop Stop" of the stock market, commodity prices remain low, and part of the national government deficits. In 2015, the international financial market "Roller Coaster" fluctuations make the investors pay more attention to volatility in the analysis of financial products. From a technical analysis point of view of the band operation, the greater the volatility, the sooner a wave cycle, investment income is relatively more objective; If you want to ensure that investment income is sustained and stable, you need to understand by what factors affect the price of the investment variety, that is to say, analyzed the varieties of investment volatility and associated factors [1-3].

THEORETICAL ANALYSIS

Correlation analysis is a central problem in multivariate financial analysis, including asset pricing, portfolio, fluctuation of conduction and overflow, risk management, and other problems. The linear correlation coefficient, Granger causality analysis method is a common method of correlation analysis [4, 5].

VAR model is used to estimate the dynamic relationship between multiple time series variable, without any prior constraints. It is a promotion of AR model, not to make an estimate of a single variable, but a set of time series variables as a system to estimate. This kind of method is put forward by the Sims, in 1980; the VAR model is short for "Vector Autoregressive Model" 6. More strictly speaking, the VAR model to each variable in the system as the lag value of the system contains all variables function to structure. At the same time the VAR model does not need to be estimated on the basis of the economic theory, establish the VAR model to time series of lag values can be incorporated into the model 7.VAR Model can be represented as:

$$y_t = \beta_0 + \sum_{i=1}^{k} \beta_i y_{t-i} + e_t \qquad (1)$$

The y_t is a column vector, consists of the t phase of the observed value. If the system contains n times series variable, y_t is n-dimensional column. The coefficient matrix e_t is $n*n$-level. e_t as a n-dimensional vector error. In a VAR model, request error term obey weakly stationary stochastic process, e_t should be white-noise process, meet: $E(e_t) = 0$, $E(e_t e_t')$, and when $(t \neq s)$, $E(e_t e_s') = 0$. e_t subject white noise process because "e_t there is no autocorrelation hypothesis", to comply with the consistency of the OLS estimates. When building the

VAR model, need to determine the number of variables and lag order number. In terms of the number of variables, if the model variables is overmuch, will produce more parameters should be estimate in the VAR system. When increasing the estimated parameters will reduce the estimation error, and reduce the accuracy of the model. At the same time, the VAR model has a strong correlation between the variables, and the precision of the model will not be affected by the variance of estimator. In terms of lag order, usually use to minimize the AIC and SC information rules to determine the optimal lag order number8.

EMPIRICAL ANALYSIS

In order to investigate the Comex Gold, Nymex Light, Sweet Crude Oil and The Dow Jones Industrial Average structure, we selected the July 18, 2011 to July 31, 2015 for Light Crude Oil, Gold consecutively and the Dow Jones Industrial Average daily closing price of empirical analysis (data from straight flush database), a total of 1054 datas.
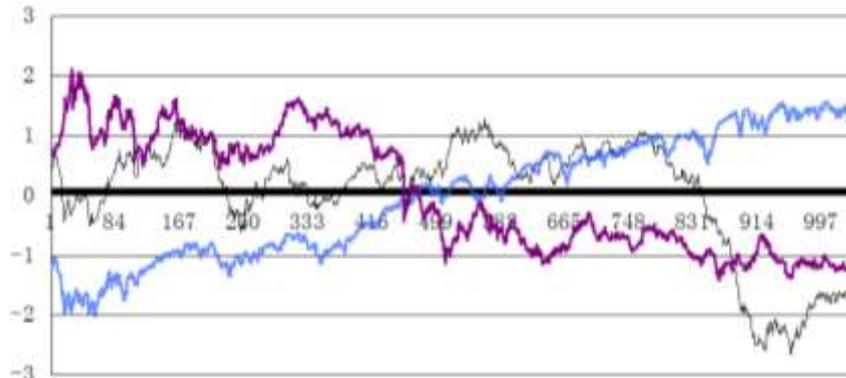

Fig-1: The sample data charts

Table 1: The descriptive statistics of sample data

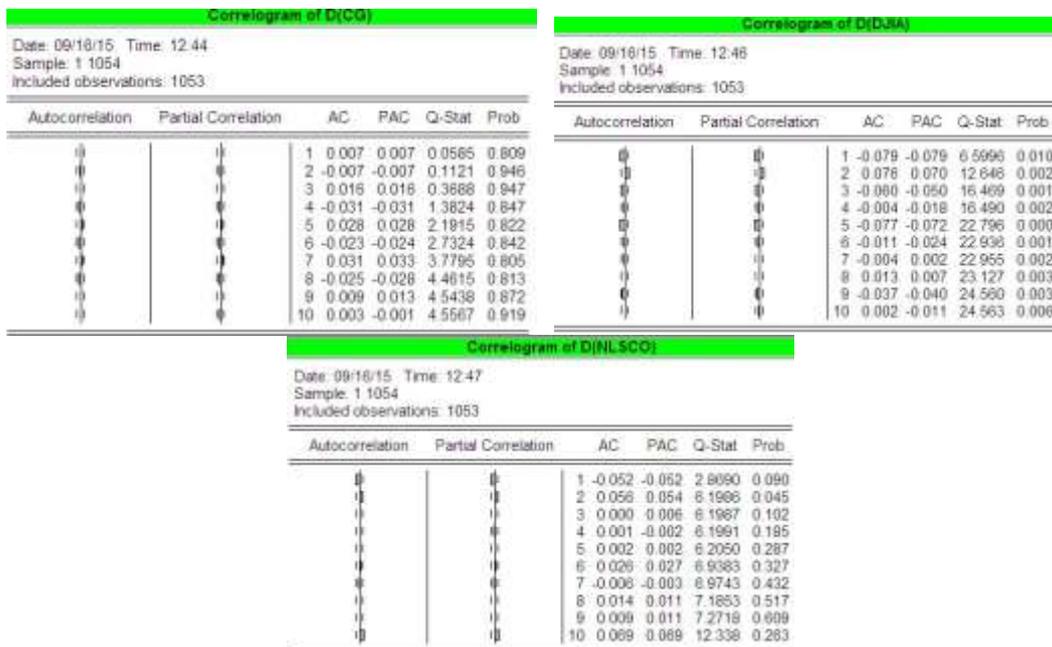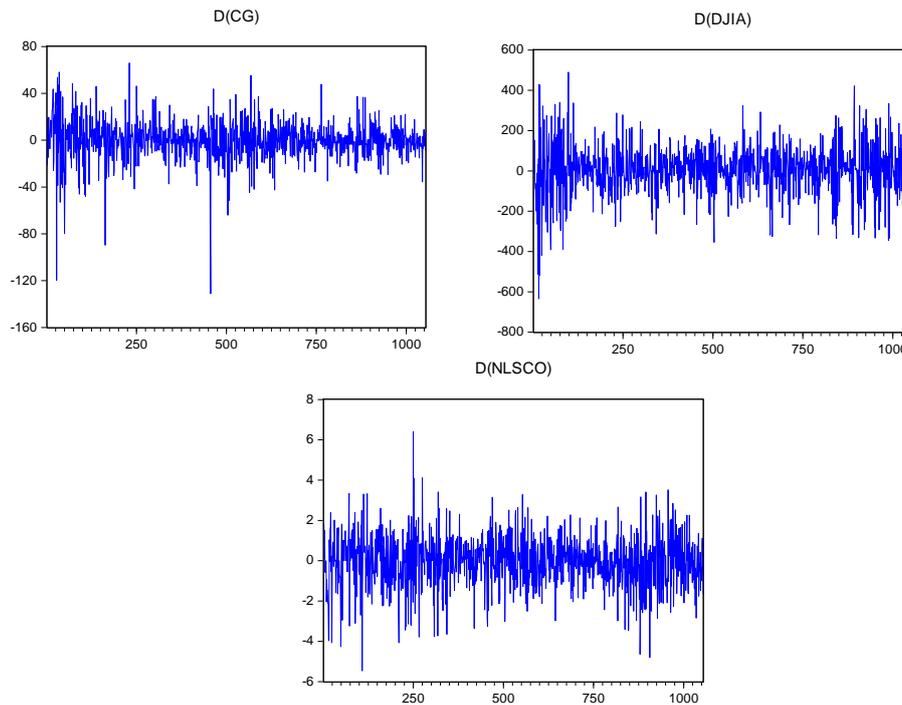|	MEAN		Standard deviations	Variance	Skewness		Kurtosis	
NLSCO	88.6	0.526	17.072	291.454	-1.287	0.075	0.492	0.151
DJIA	14973.93	65.774	2135.376	4559830.185	-0.115	0.075	-1.282	0.151
CG	1441.47	6.593	214.040	45813.284	0.237	0.075	-1.492	0.151

Fig-2: Sample data from relevant figure

Fig-3: Difference sequence diagram

We can find that the data exists heteroscedasticity of charts and statistical description, preliminary identified that three time series of first order difference is a 1-level or 2-level autoregressive process, and the 1-lever difference is smooth. Respectively to the observation sequence of the three natural logarithm, and 1-lever difference, get the sequence after the transformation. Figure 3 after transformation sequence histogram

$$\Delta u_t = 100 \times \ln\left(u_t / u_{t-1}\right) \qquad (2)$$

Including u_t as the index in the t day's closing price, the following analysis were used in the transformation after the sequence of u_t.
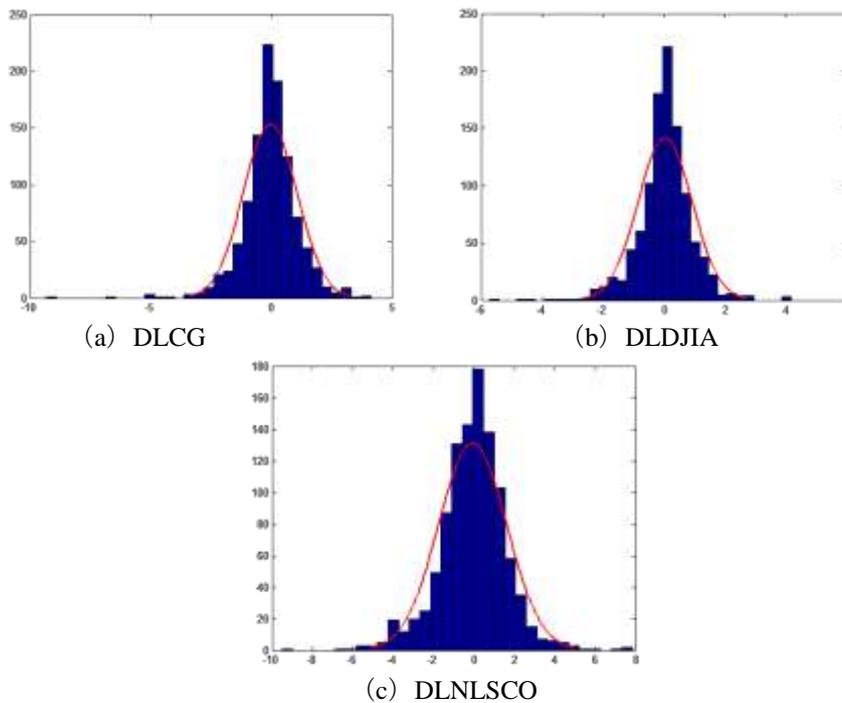

（a） DLCG

（b） DLDJIA

（c） DLNLSCO

Fig-4: The Sequence Histogram (After Transformation)

Through histogram can be found in figure 4, three sequences are not obey normal distribution, and can also be found in table 2 that three sequences were rush thick tail.

Table 2: The descriptive statistics of sample data (After Transformation)

	Standard deviations	Skewness	Kurtosis	JB
DLCG	0.011150	-0.930455	10.19885	2425.695
DLCG	0.008821	-0.491363	7.892971	1092.791
DLNLSCO	0.016775	-0.179144	5.903847	375.6006

Note: * indicates t-statistic significant under 1% confidence level. JB statistics for Jarque - Bera normality test statistics.

Through the above-mentioned certainly, sequence DLCG, DLCG, DLNLSCO does not obey the normal distribution.

CONSTRUCTION OF MODEL

Estimation model need to determine the optimal lag p of the VAR model. On the one hand, the choice of the optimal lag should not be too small, if the lag model is too small that cannot fully reflect effectively the mutual influence between variables. On the other hand, it should not be too big, can reduce the degree of freedom, and otherwise affect the validity of the estimation of model parameters. In order to select the most suitable p values, in this paper, based on the LR statistic, final prediction error information, SC information rules, AIC criterion and HQ information criterion to determine the five indicators. Test results show that the three indicators in five evaluation index support for VAR (2) model,

Table 3: inspection lag index value

LAG	OLS	LR	FPE	AIC	SC	HQ
0	-12693.44	NA	6537845	24.20675	24.22092	24.21212
1	-12661.25	64.13237	6255094	24.21923	24.21923*	24.18403*
2	-12651.53	19.30963*	6246520	24.16117*	24.26037	24.19878
3	-12645.16	12.61520	6277948*	24.16618	24.30791	24.21992
4	-12642.41	5.431433	6353220	24.17810	24.36234	24.24796

Test results show that the three indicators in five evaluation index support for VAR (2) model, the optimal lag of the VAR model is 2, VAR (2) model is set up can be determined. Model is as follows:

$$CG = 0.996 \times CG(-1) - 0.021 \times CG(-2)$$
$$+ 0.006 \times DJIA(-1) - 0.008 \times DJIA(-2)$$
$$- 0.034 \times NLSCO(-1) + 0.004 \times NLSCO(-2)$$
$$+ 75.888$$

$$(3)$$

$$DJIA = -0.095 \times CG(-1) + 0.003 \times CG(-2)$$
$$+ 0.905 \times DJIA(-1) + 0.085 \times DJIA(-2)$$
$$+ 5.743 \times NLSCO(-1) - 5.899 \times NLSCO(-2)$$
$$+ 307.138$$

$$(4)$$

$$NLSCO = 0.001 \times CG(-1) - 0.002 \times CG(-2)$$
$$+ 0.002 \times DJIA(-1) - 0.002 \times DJIA(-2)$$
$$+ 0.906 \times NLSCO(-1) + 0.091 \times NLSCO(-2) \quad (5)$$
$$+ 2.8$$

Using the unit root test to determine the stability of the VAR model, as shown in the figure below:
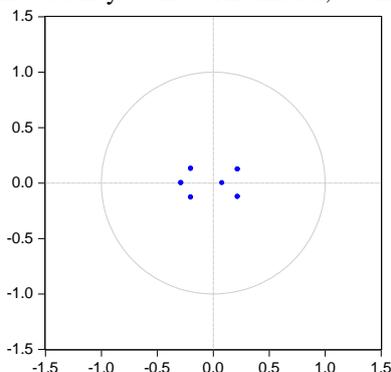

Fig-5: Unit root test

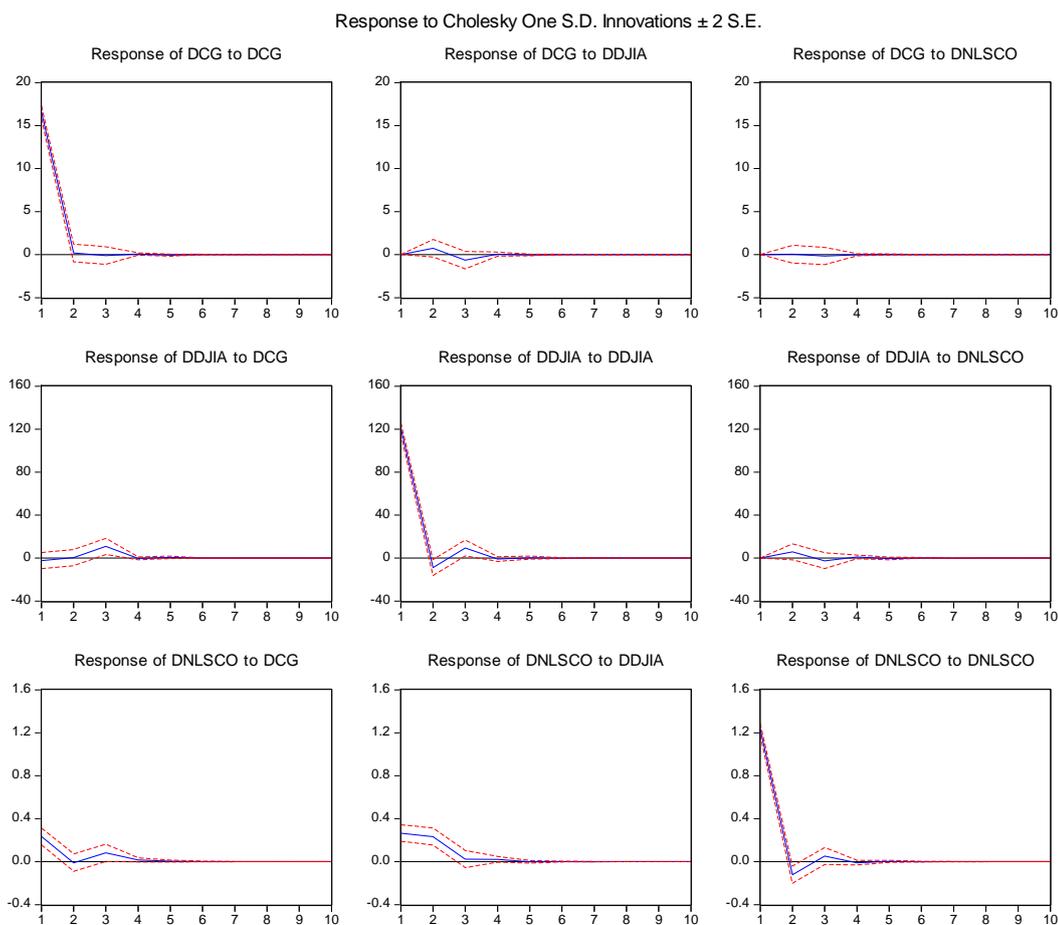Can be found by figure 5 characteristic root, are less than 1, so the VAR model is smooth.

Fig-6: Impulse response and variance decomposition analysis

The established VAR model based on correlation analysis for a long time, the following on the short-term correlation of the sequence of Granger causality test, because of the DLCG, DLDJIA and DLNLSCO has no long-term equilibrium relationship, so this paper is to focus on short-term interactions about DLCG, DLDJIA and DLNLSCO by Granger causality test results as shown in table 4:

Table 4: Granger causality test results

Primary Hypothesis	F	P	result
DLDJIA is not DLNLSCO Granger reason	17.7389	3.E-08	Reject
DLNLSCO is not DLDJIA Granger reason	0.86902	0.4197	Accept
DLCG is not DLNLSCO Granger reason	0.93745	0.3920	Accept
DLNLSCO is not DLCG Granger reason	0.27779	0.7575	Accept
DLCG is not DLDJIA Granger reason	4.38834	0.0127	Reject
DLDJIA is not DLCG Granger reason	1.79135	0.1672	Accept

The table 4 shows that under the 5% significant level, between CG and DJIA exists only CG one-way leading to the DJIA short-term relationship.

CONCLUSION

Empirical analysis show that: in the short term, CG price changes for the DJIA have prediction effect; CG price can guide the DJIA. But the DJIA price change will not have prediction effect on CG prices; DJIA can't guide the CG price changes. Similarly, between NLSCO and DJIA, is only the DJIA to NLSCO short-term one-way leading relationship. In the short term, the change of the DJIA to NLSCO prices have prediction effect, DJIA can lead NLSCO price; While NLSCO price changes, the action of the DJIA did not predict NLSCO price changes can't guide the DJIA. NLSCO between price and price of CG, there is no price of CG to NLSCO short-term price guide the relationship between each other.

Through the correlation between long-term and short-term prediction, can find the relationship between the three products, screen information is worth further research. Combined with the VAR model can specify how specific associated, how much influence degree.

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