

A Study on the Dynamic Conditional Correlation Between International Oil, Gold, and China's Stock Markets

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Abstract: In the context of globalization, China's stock market (CSM) is increasingly impacted by the risks in international financial markets, especially the two important commodities, oil and gold. This article started from the perspective of stock market styles and used the model to explore the dynamic conditional correlation between international oil, gold markets, and CSM. The study found a positive mean dynamic conditional correlation (DCC) between the international oil market and CSM, which is heterogeneous for different market styles. On average, Oil price shocks are more correlated with large-cap, value, and dividend stocks. After further dividing the sample interval, the study found that during the occurrence of external shocks, the DCC between assets generally increases. As for gold, the research also found a positive mean DCC between the international gold market and CSM, which expands when external shocks occur as well, failing to reflect its hedging properties. The research not only enriches the understanding of the linkage mechanism among financial markets but also provides an empirical basis for investors to formulate more precise risk management and investment strategies in the changing international market environment.

Keywords: China's stock market, international oil market, international gold market, dynamic conditional correlation, *DCC-GARCH* model.

1. Introduction

In the globalized economic system, the economies of countries are more and more impacted by the fluctuations in international financial markets. As China's capital market gradually opens up, the linkage between China's stock market (CSM) and the international financial markets has become increasingly closer. Oil and gold, two major commodities, play key roles in the economic and financial activities. The volatility in oil prices will impact the operating costs and profit margins of enterprises, thus affecting their economic decisions and stock performances. Gold is generally considered to have the function of protecting against inflation, preventing unknown risks, and serving as a safe haven, so reasonable allocation of gold assets can help investors diversify investment risks and increase yields. In the past two decades, the world has experienced many external shocks, and the occurrence of extreme events has increased the volatility and investment risks of CSM. Therefore, assessing the linkage between oil, gold and the stock market (OGSM) can help explore more advanced risk management and investment strategies.

Extensive research has been done on the correlation between OGSM. Filis used *DCC-GARCH* model to show a dynamic correlation between oil prices and the stock markets of both oil exporting and importing countries [1]. Wen found that oil price volatility directly caused risk spillovers to the CSM based on the *DCC-MGARCH* model [2]. Zhu found that the response of industry stock market returns to actual oil price volatility is heterogeneous [3]. Syed and Perry applied *DCC*, *ADCC* and *GO-GARCH* models and found that oil can hedge the risks in emerging stock markets in most conditions, while sometimes the hedging effect of gold is better [4]. Walid used wavelet analysis to find that the BRICS stock markets were linked to WTI oil prices in the long run, and this linkage was particularly evident during the financial crisis, but the study did not find empirical support for the linkage between gold and stock markets in BRICS countries, suggesting that gold can be used as a hedging asset for BRICS countries to resist extreme market fluctuations [5].

However, some scholars are skeptical about the hedging role of gold. Hood and Malik conducted empirical analysis of the US stock market and found that under normal circumstances, gold can be used as a weak hedging asset, but under extreme market volatility, the negative connection between gold and stock markets does not exist, that is, the hedging effect of gold disappears during crisis [6]. Chen's empirical research found a positive linkage between gold and stock yields, so gold assets cannot provide a hedging function for stock assets [7]. Erband also believes that in periods when financial markets face greater risks, gold may show a certain positive correlation with the stock market, so it may not be a reliable hedging asset [8].

Based on previous literature, it can be found that although much research has been done on the correlation between OGSM, the study objects are mainly concentrated on the overall market and particular industries, and the influence of the two commodities on different market styles has not been mentioned. Besides, scholars still disagree on the hedging role of gold.

Given these shortcomings, this paper selects stock indexes including SSE 50, CSI 300, CSI 500, CSI 1000, GZ Growth, GZ Value, and CSI Dividend as study objects, further divides the overall sample interval into sub-samples when external shocks occur, and uses the *DCC-GARCH* model to characterize the dynamic conditional correlation (DCC) and heterogeneity between international oil, gold markets, and CSM.

The innovations of this paper can be summarized as follows: On the one hand, starting from different stock market styles, the research perspective is refined into styles of large and small cap, growth and value, and dividend, to explore the DCC and its heterogeneity between assets. On the other hand, further division is made to the sample interval to explore the hedging properties of gold during the period of external shocks.

2. Theoretical Analysis and Hypothesis

Since oil and gold have different asset attributes and market reaction mechanisms, so on average, oil has greater correlations with the stock market than gold. Considered as a hedging asset, gold is usually used to protect investor's wealth when the market is unstable or economic uncertainty increases, so it has a lower correlation with the stock market than oil.

Martínez's industry-level study of the Spanish stock market confirmed that oil prices do not play an important role in the consumption, technology, real estate, and utility industries. On the contrary, the energy, construction, and banking industries are most affected by volatility in the oil market [9]. Jin also discussed in detail the impact that international oil prices have on the 14 industry stock returns in China, finding a positive impact on the oil and gas industry, and a negative for automobile and parts, construction and materials, finance, personal and household products industry and so on [10]. Therefore, based on scholars' research results as well as the industry composition of different stock market style indexes, it makes the following theoretical assumptions.

Oil is usually more correlated with large-cap stocks than with small and medium ones. Large-cap stocks are composed of blue-chip stocks with large market capitalization and good liquidity, and these companies are often closely linked to the macroeconomic cycle. Since investors' expectations for the oil market are usually linked to expectations for economic conditions, and large-cap stocks occupy an important position in the economy, their stock prices are more susceptible to such sentiments and expectations. In addition, since oil is an important energy source for the global economy, its price fluctuations will directly affect the operating costs and profits of large energy and chemical companies, and thus affect their stock performance. In contrast, small-cap stocks are more concentrated in industries that are less sensitive to fluctuations in the oil market, such as technology, media, telecommunications (TMT), and so on, so their dynamic correlation with oil is relatively small.

Compared with growth stocks, oil, and value stocks are usually more correlated. Value stocks are composed of companies with relatively low valuations, high dividend rates, and stable profit records. These companies tend to be concentrated in traditional, mature industries such as energy, industry, and finance, which are more sensitive to macroeconomic conditions or have direct relationships with oil. Growth stocks usually refer to companies with higher valuations and growth potential. They are mostly concentrated in innovation-driven industries like TMT and consumption. The growth of these industries relies more on innovation, technological progress, and consumer demands, making them relatively less sensitive to fluctuations in oil markets.

Dividend stocks are usually highly correlated with oil. Dividend stocks are mostly concentrated in the coal, transportation, steel, and chemical sectors, which are closely related to the fluctuations in oil markets.

3. Model Construction and Data Selection

3.1. Model Construction

The paper uses *DCC-GARCH* model proposed by Engle, which can capture the correlation between assets over time, to characterize the DCC between international OGSM [11]. The method is to estimate the single variable *GARCH* model, and then is the DCC coefficient between variables. The specific model is set as follows:

The model assumes the return r_t on an asset follows the following distribution:

$$r_t | \Omega_{t-1} \sim N(0, H_t) \quad (1)$$

$$H_t = D_t R_t D_t \quad (2)$$

$$D_t = \text{diag}(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \dots, \sqrt{h_{NN,t}}) \quad (3)$$

$$R_t = (\text{diag}(Q_t))^{-\frac{1}{2}} Q_t (\text{diag}(Q_t))^{-\frac{1}{2}} \quad (4)$$

Among them, r_t is the asset return rate, Ω_{t-1} is the information set at the moment t , R_t is the DCC coefficient matrix, D_t is a diagonal matrix composed of conditional standard deviations $\sqrt{h_{11,t}}$, the conditional variance $h_{11,t}$ is fitted by the single variable *GARCH* model, and H_t is the conditional covariance matrix.

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \quad (5)$$

Among them, Q_t is the covariance matrix, \bar{Q} is the unconditional covariance after residual standardization, and ε is the standardized residual. a is the standardized residual coefficient of lag 1, and b is the conditional variance coefficient of lag 1. Both are non-negative and satisfy $a + b < 1$.

Therefore, the DCC coefficient between two financial variables under the model *DCC-GARCH*(1,1) is defined as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \quad (6)$$

3.2. Sample Data Selection and Descriptive Statistics

The sample data selected in this paper comes from the iFind database. As one of China's leading financial data service providers, the iFind database is widely recognized for its comprehensive data coverage and high accuracy. To measure different stock market styles, this paper selects seven major stock indexes: SSE 50, CSI 300, CSI 500, CSI 1000, GZ Value, GZ Growth, and CSI Dividend. Among them, SSE 50 and CSI 300 respectively represent the top 50 and 300 most influential large-cap enterprises in CSM. CSI 500 reflects the overall performance of 500 medium-sized enterprises, and CSI 1000 covers the performance of small enterprises in the market. CSI Value, CSI growth, and CSI Dividend represent the performance of value, growth, and dividends stocks in the market respectively. The daily price data of WTI oil London gold is selected, which are influential commodity benchmarks in the international financial markets. By analyzing the above data, we can more accurately and comprehensively explore the DCC between international oil and gold markets and CSM, especially different market styles.

The article takes the logarithms of the daily closing prices of stock indexes, WTI oil, and London gold during the sample period, and then performs a difference to obtain the logarithmic rate of return. The descriptive statistics are shown in Table 1. On average, GZ Value and WTI oil obtain the highest and lowest return rates respectively. In terms of standard deviation, WTI oil and London gold have the highest and lowest volatility respectively. The skewness of the sample data is all less than 0 and the kurtosis is greater than 3. The JB statistics all reject the null hypothesis of normal distribution at the 1% significance level. Therefore, the returns of WTI oil, London gold and CSM indexes are characterized by negative skewness, leptokurtosis, fat tails and non-normality.

Next, the paper uses the ADF test, LB test, and ARCH-LM test to check the stationarity, autocorrelation, and conditional heteroskedasticity of the data to verify whether it is suitable for *DCC-GARCH* model. The results in Table 2 show that the return series all reject the null hypothesis at the 1% significance level, that is, the series is stationary and has autocorrelation and conditional heteroskedasticity.

Table 1: Descriptive statistics

Variables	mean	min	max	sd.	skewness	kurtosis	Jarque-Bera test
SSE_50	0.0211	-9.9497	9.2332	1.5711	-0.2743	5.1197	5606.31***
CSI_300	0.0253	-9.6949	8.9310	1.5630	-0.5025	4.8396	5166.33***
CSI_500	0.0329	-9.3791	9.4147	1.7842	-0.8489	4.3931	4690.53***
CSI_1000	0.0328	-9.1961	9.3116	1.8577	-0.8587	3.6131	3384.19***
GZ_growth	0.0282	-9.7495	9.0567	1.6434	-0.5263	3.8965	3444.74***
GZ_value	0.0352	-9.8503	9.0024	1.5604	-0.5957	5.4686	6623.99***
CSI_div	0.0338	-9.8865	8.8237	1.5866	-0.6622	5.3369	6393.77***
WTI_oil	0.0118	-56.8589	47.0004	2.7829	-1.0475	63.0488	841507.48***
London_gold	0.0334	-9.5258	10.7960	1.0688	-0.2741	7.0596	10602.17***

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 2: Correlation test results

Variables	ADF test	Ljung-Box test (lag=50)	ARCH-LM test
SSE_50	-11.26***	119.50***	126.25***
CSI_300	-11.59***	114.11***	155.16***
CSI_500	-17.96***	118.49***	288.04***
CSI_1000	-38.16***	129.27***	296.09***
GZ_growth	-14.53***	98.85***	121.75***
GZ_value	-11.86***	112.38***	215.64***
CSI_div	-12.50***	117.25***	225.95***
WTI_oil	-10.76***	316.23***	153.52***
London_gold	-40.42***	69.48**	74.94***

* p < 0.1, ** p < 0.05, *** p < 0.01

4. Empirical Results

4.1. Mean DCC

After correlation tests, *DCC-GARCH* model can be established. Then according to formula (6), the DCC coefficients between WTI oil, London gold, and stock index returns can be estimated respectively. The larger the value, the stronger the correlation between WTI oil or London gold and CSM. The article calculates the mean of the DCC coefficients to analyze from an overall perspective. The results are shown in Table 3.

It can be found that DCC coefficients between gold and stock indexes are generally higher than those between oil, and there are obvious differences in the coefficients of oil, while for gold those are relatively stable.

From the perspective of market styles, the coefficients between oil and large-cap stocks are higher than those between small-cap stocks; The coefficient between oil and value stocks is higher than that between growth stocks; In addition, the coefficient between dividend stocks and oil is the highest.

Table 3: Mean DCC between WTI oil, London gold, and stock market style indexes

Variables	WTI_oil	London_gold
SSE_50	0.0860	0.0570
CSI_300	0.0787	0.0659
CSI_500	0.0726	0.0655
CSI_1000	0.0642	0.0652
GZ_growth	0.0667	0.0660
GZ_value	0.0934	0.0640
CSI_div	0.0938	0.0749

4.2. DCC During External Shocks

Furthermore, to specifically analyze the time-varying attributes in DCC between WTI oil, London gold, and CSM in different periods, the paper gives the time series changes of the DCC coefficients, as shown in Figure 1.

It can be found that during the 2008 financial crisis, the 2020 COVID-19 pandemic, and the 2022 Russia-Ukraine conflict, the DCC coefficients between WTI oil, London gold, and CSM generally increased significantly.

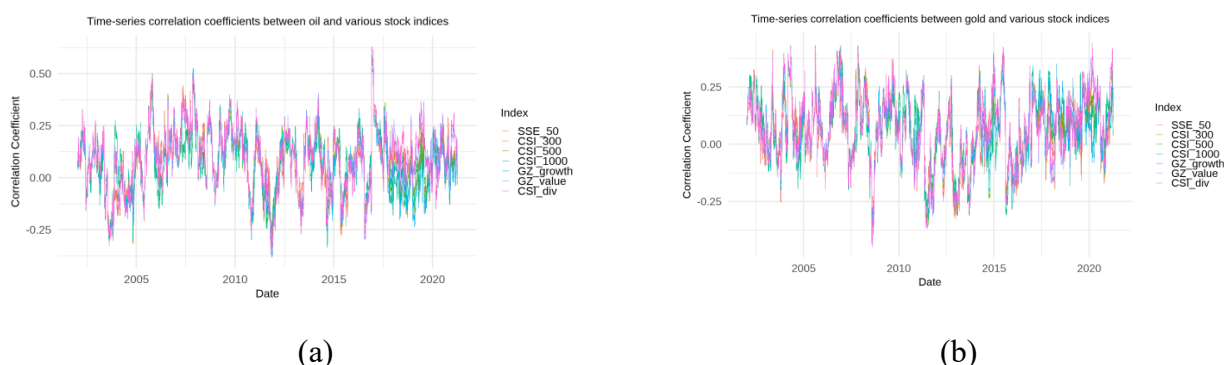


Figure 1: Time-varying DCC coefficients. (a) DCC coefficients between WTI oil and stock market style indexes; (b) DCC coefficients between London gold and stock market style indexes (original).

Therefore, the article further measures the percentage changes of the correlation during the three time periods when external shocks occur relative to the full sample results. From the data in Table 4, it can be found that the DCC between assets has increased significantly during crisis and pandemic. However, during conflict, the energy crisis caused oil prices to rise and volatility to increase, resulting in a decrease in its correlation with most stock indexes.

Table 4: Percentage change in DCC coefficients between oil and stock market style indexes when external shocks occur

Variables	2008 financial crisis	2020 COVID-19 pandemic	2022 Russia-Ukraine conflict
SSE_50	18.05%	6.44%	-27.18%
CSI_300	11.65%	1.94%	-54.47%
CSI_1000	-12.37%	39.86%	-39.23%
GZ_growth	6.08%	21.11%	-99.45%
GZ_value	17.19%	-2.18%	-102.48%
CSI_div	-8.01%	11.50%	25.35%

4.3. The Hedging Properties of Gold

Some studies have shown that in recent years, gold investment for speculative purposes has increased, and investors' speculative behavior may undermine the hedging asset role of gold [12]. In addition, the accelerated financialization of the commodity market has also made gold assets behave more like stocks, and the hedging status of gold seems to be disappearing [13-15].

The data in Table 5 can confirm the above views. Regardless of the full sample period or the external shock periods, the mean DCC between gold and stock indexes is positive, and it has expanded in most shock periods. Therefore, gold has not played the role of a hedging asset well.

Table 5: Percentage change in DCC coefficients between gold and stock market style indexes when external shocks occur

Variables	2008 financial crisis	2020 COVID-19 pandemic	2022 Russia-Ukraine conflict
SSE_50	86.66%	-14.37%	66.91%
CSI_300	80.82%	-6.06%	49.39%
CSI_1000	74.26%	10.60%	48.00%
GZ_growth	72.54%	36.04%	49.17%
GZ_value	88.62%	15.67%	38.81%
CSI_div	77.84%	-48.76%	54.24%

5. Conclusion

The article aims to explore the DCC between international oil, gold, and CSM, especially different market styles. The paper selects SSE 50, CSI 300, CSI 500, CSI 1000, GZ Growth, GZ Value, and CSI Dividend indexes as research objects, representing different market styles, and uses *DCC-GARCH* model to quantify the DCC coefficients between assets.

On the one hand, this study found that there are positive mean DCC between the international oil market and CSM, and the correlation will be significantly enhanced when external shocks occur. On the other hand, whether it is under the full sample or during external shocks, the mean DCC between gold and stock indexes is positive and expands in most shock ranges. Therefore, gold fails to play the role of a hedging asset.

Overall, the conclusions of this paper not only enrich the research on the linkage between international commodities and CSM but also provide empirical support for how to effectively identify and assess financial market risks in the context of globalization. Future research can further explore the dynamic changes in risk spillover effects, and provide more empirical support for real-world investment decisions and policymaking.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

- [1] Degiannakis, S., Filis, G., & Floros, C. (2011). *Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries*. *International Review of Financial Analysis*, 20, 152–164.
- [2] Wen, Y., Wang, J., & Cheng, T. (2015). *Research on spillover effects between domestic stock market and international stock market, commodity market*. *International Financial Research*, 31, 31–43.
- [3] Zhu, H., Guo, Y., You, W., & Xu, Y. (2016). *The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach*. *Energy Economics*, 55, 30–41.
- [4] Basher, S. A., & Sadorsky, P. (2016). *Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH*. *Energy Economics*, 54, 235–247.
- [5] Mensi, W., Hkiri, B., Al-Yahyaee, K. H., & Kang, S. H. (2018). *Analyzing time–frequency co-movements across gold and oil prices with BRICS stock markets: A VaR based on wavelet approach*. *International Review of Economics & Finance*, 54, 74–102.
- [6] Hood, M., & Malik, F. (2013). *Is gold the best hedge and a safe haven under changing stock market volatility?* *Review of Financial Economics*, 22, 47–52.
- [7] Chen, Q. (2013). *Is the gold market a safe haven for investors? An empirical study based on gold, stock, and bond markets*. *Zhejiang Finance*, 56, 56–59.
- [8] Erb, C. B., & Harvey, C. R. (2013). *The golden dilemma*. *Financial Analysts Journal*, 69, 10–42.
- [9] Moya-Martinez, P., Ferrer-Lapena, R., & Escribano-Sotos, F. (2014). *Oil price risk in the Spanish stock market: An industry perspective*. *Economic Modelling*, 37, 280–290.
- [10] Jin, H., & Jin, L. (2010). *The impact of international oil prices on China's stock market: An empirical analysis based on industry data*. *Financial Research*, 2, 173–187.
- [11] Engle, R. (2002). *Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models*. *Journal of Business & Economic Statistics*, 20(3), 339–350.
- [12] Bekiros, S., Boubaker, S., Nguyen, D. K., & Uddin, G. S. (2017). *Black swan events and safe havens: The role of gold in globally integrated emerging markets*. *Journal of International Money and Finance*, 73, 317–334.
- [13] Adams, Z., & Glück, T. (2015). *Financialization in commodity markets: A passing trend or the new normal?* *Journal of Banking & Finance*, 60, 93–111.
- [14] Tan, D., & Tian, L. (2022). *Is gold a “safe haven” for the stock market? Based on a dynamic conditional correlation mixed-frequency data sampling model*. *Chinese Management Science*, 30, 14–24

- [15] Klein, T. (2017). *Dynamic correlation of precious metals and flight-to-quality in developed markets*. *Finance Research Letters*, 23, 283–290.