Analysis of the return linkages among international crude oil futures, Chinese stock market and US stock market based on VAR model

Fangying Dong

Msc in Finance, EM-Lyon Business School, 23 avenue Guy de Collongue, CS 40203, 69134, Ecully cedex-France

dsdomj@163.com

Abstract. Crude oil, as a primary global energy resource, plays a pivotal role in influencing global financial landscapes, especially in major economies like China and the US. Despite extensive studies, a comprehensive analysis intertwining the three areas—crude oil prices, the Chinese stock market, and the US stock market—using the Vector Autoregression (VAR) model is lacking. This study bridges that gap, examining the interactions among international crude oil futures returns, the Shanghai Composite Index and the S&P 500 Index using 2,954 data sets from January 2011 to August 2023. Findings reveal a strong interconnection with crude oil futures significantly impacting both stock markets. Following disturbances, all markets revert to baseline states, with positive crude oil futures briefly boosting stock markets. However, stock market growth may precede a fall in crude oil futures. Although quantitative, the study's model may not fully align with real-world economic dynamics and carries potential overfitting risks due to its extensive lag order.

Keywords: Crude oil, Stock Market, VAR model, Return.

1 Introduction

Crude oil stands as the paramount energy resource worldwide, underpinning a myriad of economic activities. Its price dynamics not only resonate within energy-centric sectors but also have the potential to instigate cascading effects throughout global financial landscapes. In particular, when considering China and the United States and, the largest markets in the global economy, these cascading effects can usher in profound economic implications.

The nexus between crude oil price trajectories and stock market valuations has been a focal point of academic inquiry. Liu et al. uncoverd a notable dynamic correlation and risk transmission between the oil market and the U.S. stock market, emphasizing the pronounced time-varying positive association between their respective implied volatility returns [1]. Jiang & Yoon demonstrated that oil prices significantly influence stock returns, especially in oil-exporting countries[2].

K. Elbagory et al. (eds.), *Proceedings of the 9th International Conference on Financial Innovation and Economic Development (ICFIED 2024)*, Advances in Economics, Business and Management Research 281,
https://doi.org/10.2991/978-94-6463-408-2_62

The VAR model, since its championing by Sims for macro-econometric endeavors, has ascended to a prominent stature across diverse disciplines, spanning economics to finance [3]. Shahrestani & Rafei examined the effects of oil price shocks on Tehran Stock Exchange returns using Markov switching VAR models [4]. Xie probed into the spillover ramifications of the international crude oil futures domain on China's burgeoning energy stock market using the VAR methodology [5]. Chen and Hao orchestrated an analysis harnessing the VAR paradigm to fathom the synchronicities between China's crude oil futures valuations and sector-specific stock indices [6]. In a recent endeavor, Li elucidated the dynamics of price discovery and volatility spillovers between China's and international crude oil futures through the VAR lens [7].

Despite the wealth of literature delineating the intersections of crude oil prices with either the Chinese or US stock markets, a holistic VAR-based dissection that seamlessly ties all three spheres remains elusive. This research seeks to bridge this gap, providing a more granular understanding for policymakers and the investing community of the intricate tapestry linking these markets. This study embarks on an empirical exploration of the interconnections between international crude oil futures, the Chinese equity market, and the US equity market through the prism of the Vector Autoregression (VAR) model. The overarching goal is to enrich the comprehension of these market interplays and furnish investors with astute decision-making insights.

2 Methodology

To measure the interconnectedness between international crude oil futures and the stock markets of China and the US, as well as their mutual influence on returns, an attempt was made to construct a mathematical model for analyzing the three sets of variables together. Since all three sets of variables are time series data, there is interaction and influence between every two sets of variables, and each set of variables also has endogenous effects, a three-variable VAR model was adopted for modeling.

For a general VAR model of lags order p, denoted as $VAR(p)$, for a k-dimensional time series Y_t is written as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t \tag{1}$$

where Y_t is a $k*1$ vector of endogenous variables at time *t*; A_i for $i = 1,\dots,p$ are $k*k$ matrices of coefficients; u_t is a $k*1$ vector of error terms. The error terms u_t are assumed to be white noise and are not correlated with their lagged values or with past values of Y_t.

In this paper, because 3 time series are considered, so we have:

$$Y_t = \begin{bmatrix} LCO \\ SSEC \\ US500 \end{bmatrix} \tag{2}$$

where LCO, $SSEC$ and $US500$ denote the daily return of LCO, SSEC and US500.

3 Empirical Analysis

This research leverages the daily trading data of LCO, SSEC and US500 spanning January 1, 2011, to August 1, 2023. These data subsets serve as proxies for the performance trajectories of international crude oil futures, the Chinese equity market, and the U.S. equity landscape during this period. Post the exclusion of incongruent trading days, a total of 2954 data points are analyzed. The data sources are attributed to investing.com.

3.1 Descriptive Analytics

Figure 1 highlights LCO's conspicuously broader return fluctuations as opposed to the more constrained oscillations of SSEC and US500. Yet, volatility clustering is a recurrent theme across all three datasets.

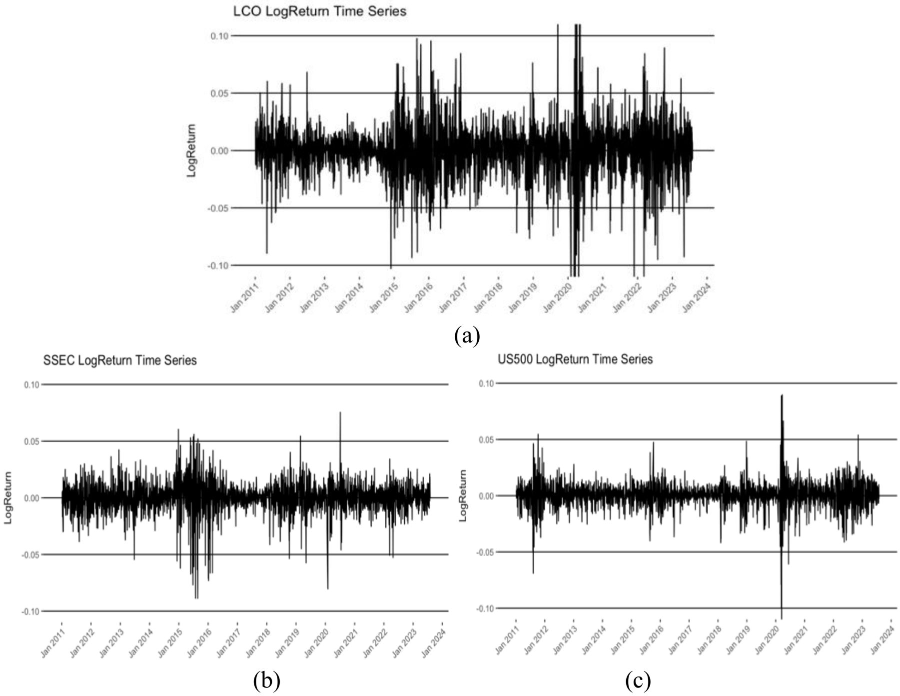


Fig. 1. Daily Returns of LCO, SSEC, and US500

Tables 1 proffer a quantitative deep dive into the descriptive statistics of LCO, SSEC, and US500 returns. This table corroborate the graphical interpretations — the J-B statistics signify a non-normal distribution for these datasets. The return dynamics skew leftward. Moreover, all three datasets exhibit pronounced kurtosis, rendering them leptokurtotic with a predisposition for fat tails.

Table 1. Descriptive statistics of Returns of LCO, SSEC, US500

	LCO return	SSEC return	US500 return
Mean	-0.00003	0.00005	0.00043
Maximum	-0.27976	0.07548	0.08968
Minimum	0.19077	-0.08873	-0.12765
Standard Deviation	0.02444	0.01301	0.01134
Skewness	-0.93000	-0.77553	-0.71759
Kurtosis	19.36425	9.67295	17.08333
J-B Statistic. X-squared	33374.85000	5774.84700	24657.52000

3.2 Stationarity Assessment

To ensure the reliability and validity of modeling endeavors on the aforementioned datasets, ascertaining their stationarity is imperative. To this end, the Augmented Dickey-Fuller (ADF) test [8] is employed to gauge the stationarity of the returns of LCO, SSEC, and US500. Table 3 delineates the outcomes of this assessment.

Table 2 reveals a robust rejection of the null hypothesis. With t-statistic readings of -37.54, -37.88, and -37.86 respectively, complemented by a p-value verging on zero, it's unequivocal that the returns of LCO, SSEC, and US500 are devoid of a unit root. This infers the inherent stationarity of all three data sequences.

Table 2. ADF test for returns of LCO, SSEC and US500

	LCO	SSEC	US500
t-statistic	-37.543	-37.884	-37.856
p-value	0.000	0.000	0.000

3.3 VAR Model Implementation

In this section, a VAR model based on the return datasets for the three financial instruments is constructed.

Initiating this process is to determine the appropriate lag order for the VAR model. Some of the criteria for this selection, represented by AIC, HQ, SC, and FPE values, are detailed in Table 3. Observably, the AIC reaches its minimum at a lag order of 9. Given the relatively minimized SC and HQ values, a lag order of 9 is consequently adopted for the VAR model formulation.

Table 3. Results of lag order selection

Lag	AIC	HQ	SC	FPE
6	-25.26063	-25.21668	25.13856	1.07E-11
7	-25.26447	-25.21393	25.1241	1.07E-11
8	-25.26825	-25.21111	25.10957	1.06E-11
9	-25.27056	-25.20683	25.09356	1.06E-11
10	-25.26665	-25.19633	25.07135	1.06E-11

Figure 2 illustrates the estimations derived from this model. A perusal of the table reveals that at varied lags, the return patterns of LCO, SSEC, and US500 exhibit nuanced interdependencies.

	LCO					SSEC					US500				
	Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)	
lco.l1	8.346e-04	1.958e-02	0.043	0.96601		9.284e-03	1.035e-02	0.897	0.36994		-1.108e-02	8.967e-03	-1.236	0.216612	
ssec.l1	4.957e-03	3.560e-02	0.139	0.88927		-1.222e-02	1.882e-02	-0.649	0.51630		-6.388e-03	1.630e-02	-0.392	0.695188	
us500.l1	4.226e-03	4.294e-02	0.098	0.92161		1.896e-01	2.270e-02	8.353	< 2e-16	***	-9.842e-02	1.966e-02	-5.005	5.91e-07	***
lco.l2	2.102e-02	1.958e-02	1.074	0.28304		8.632e-04	1.035e-02	0.083	0.93354		2.928e-02	8.965e-03	3.266	0.001104	**
ssec.l2	-1.331e-02	3.555e-02	-0.374	0.70821		-6.563e-03	1.879e-02	-0.349	0.72697		-1.489e-02	1.628e-02	-0.915	0.360370	
us500.l2	5.824e-02	4.366e-02	1.334	0.18229		7.070e-02	2.308e-02	3.063	0.00221	**	5.287e-02	1.999e-02	2.645	0.008225	**
lco.l3	-2.590e-02	1.959e-02	-1.322	0.18620		-7.349e-03	1.036e-02	-0.710	0.47799		3.001e-02	8.970e-03	3.345	0.000833	***
ssec.l3	-4.539e-02	3.554e-02	-1.277	0.20168		-4.345e-04	1.879e-02	-0.023	0.98155		-1.425e-02	1.627e-02	-0.875	0.381375	
us500.l3	7.369e-03	4.371e-02	0.169	0.86611		4.164e-02	2.311e-02	1.802	0.07159	.	-3.270e-02	2.001e-02	-1.634	0.102387	
lco.l4	2.962e-02	1.955e-02	1.516	0.12973		2.539e-03	1.033e-02	0.246	0.80590		-1.518e-02	8.950e-03	-1.696	0.089916	.
ssec.l4	-6.550e-02	3.553e-02	-1.843	0.06537	.	4.038e-02	1.878e-02	2.150	0.03166	*	2.333e-02	1.627e-02	1.434	0.151732	
us500.l4	6.720e-02	4.366e-02	1.539	0.12386		-1.856e-02	2.308e-02	-0.804	0.42146		-4.315e-02	1.999e-02	-2.158	0.030988	*
lco.l5	2.746e-02	1.955e-02	1.405	0.16025		-6.871e-03	1.033e-02	-0.665	0.50621		4.001e-03	8.952e-03	0.447	0.654967	
ssec.l5	-3.247e-02	3.557e-02	-0.913	0.36139		-3.597e-02	1.880e-02	-1.913	0.05588	.	-1.650e-02	1.629e-02	-1.013	0.311153	
us500.l5	-9.027e-02	4.373e-02	-2.064	0.03906	*	3.970e-02	2.312e-02	1.717	0.08601	.	-7.895e-03	2.002e-02	-0.394	0.693383	
lco.l6	-6.352e-02	1.947e-02	-3.262	0.00112	**	-1.539e-02	1.030e-02	-1.494	0.13516		-1.372e-02	8.918e-03	-1.539	0.123964	
ssec.l6	-1.717e-02	3.557e-02	-0.483	0.62930		-2.647e-02	1.880e-02	-1.408	0.15923		2.841e-03	1.629e-02	0.174	0.861540	
us500.l6	2.157e-01	4.362e-02	4.944	8.07e-07	***	9.737e-03	2.306e-02	0.422	0.67288		-3.910e-02	1.997e-02	-1.958	0.050357	.
lco.l7	-2.238e-03	1.949e-02	-0.115	0.90860		1.618e-02	1.030e-02	1.571	0.11636		-1.112e-02	8.924e-03	-1.246	0.212892	
ssec.l7	4.651e-02	3.555e-02	1.308	0.19087		2.078e-02	1.880e-02	1.106	0.26902		-1.091e-02	1.628e-02	-0.670	0.502702	
us500.l7	1.384e-01	4.375e-02	3.163	0.00158	**	8.330e-03	2.313e-02	0.360	0.71877		6.062e-02	2.003e-02	3.026	0.002501	**
lco.l8	-7.116e-03	1.951e-02	-0.365	0.71529		-1.643e-02	1.031e-02	-1.593	0.11121		1.751e-02	8.932e-03	1.960	0.050052	.
ssec.l8	-1.066e-02	3.553e-02	-0.300	0.76408		3.785e-02	1.878e-02	2.015	0.04395	*	-9.994e-04	1.627e-02	-0.061	0.951019	
us500.l8	-1.095e-01	4.373e-02	-2.503	0.01237	*	-1.326e-02	2.312e-02	-0.573	0.56638		-7.141e-02	2.003e-02	-3.566	0.000368	***
lco.l9	3.057e-02	1.952e-02	1.566	0.11745		2.892e-03	1.032e-02	0.280	0.77937		9.788e-03	8.940e-03	1.095	0.273649	
ssec.l9	-3.958e-03	3.503e-02	-0.113	0.91005		1.139e-02	1.852e-02	0.615	0.53859		5.458e-03	1.604e-02	0.340	0.733651	
us500.l9	-1.264e-01	4.341e-02	-2.913	0.00361	**	-3.018e-03	2.295e-02	-0.132	0.89537		4.468e-02	1.988e-02	2.248	0.024668	*
const	-5.721e-04	9.011e-04	-0.635	0.52555		-1.387e-04	4.764e-04	-0.291	0.77091		4.745e-04	4.126e-04	1.150	0.250255	
trend	3.109e-07	5.258e-07	0.591	0.55439		4.276e-08	2.780e-07	0.154	0.87775		1.077e-08	2.408e-07	0.045	0.964339	

Fig. 2. VAR Estimation Results

Note: indicates that the coefficients are significant at the 10% significance level, * is 5%, ** is 1%, and *** is 0.1%.

While the presence of numerous statistically indistinct coefficients is acknowledged, it doesn't detract from the overarching robustness of the VAR model. To ensure the model's stability, a characteristic root examination was undertaken, with results portrayed in Figure 3. The findings indicate that all characteristic roots are comfortably nested within the unit circle, corroborating the stability of the VAR model, and thus paving the way for subsequent analyses.

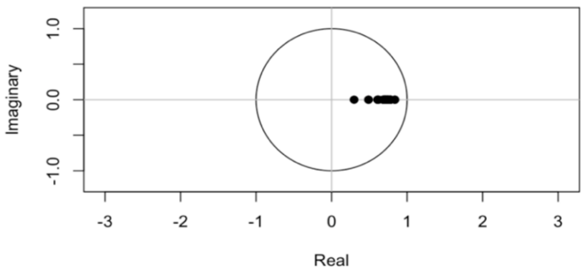


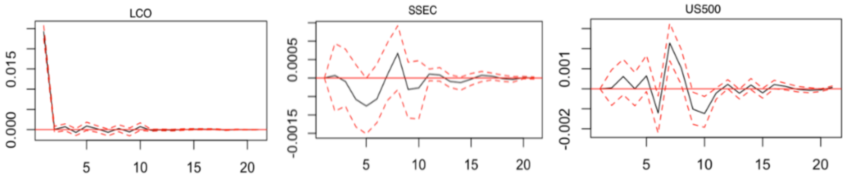
Fig. 3. Roots of the VAR Characteristic Roots

3.4 Impulse Response Analysis

To delve deeper into the interconnectedness and mutual influence of the three data sets, based on the established VAR model, impulse response analysis spanning 20 periods is carried out [9, 10]. Figures 4 to 6 encapsulate the analytical outcomes.

3.4.1 Crude oil futures returns.

As shown in Figure 4, for the crude oil futures returns, post external stimulus, there's a pronounced influence from their inherent dynamics during the inaugural period. This influence attenuates rapidly, nearing a negligible impact post the subsequent period. The Shanghai Composite Index's impact on crude oil futures predominantly spans from periods 2 to 11, registering a negative trend from periods 2 through 7. The S&P 500's influence on crude oil futures is observed from periods 1 to 11, with a conspicuous dip in the 6th period. Both indices' effects on the crude oil futures abate to near irrelevance post the 11th period.

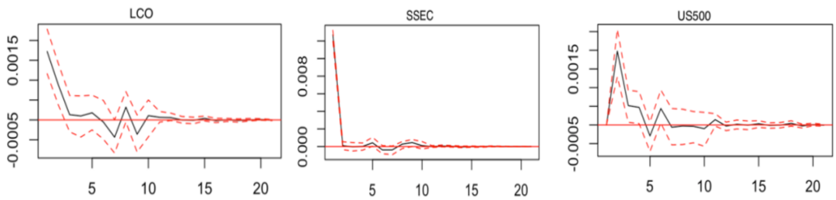


(a) (b) (c)

Fig. 4. Impulse Response Function Results (LCO)

3.4.2 Shanghai Composite Index.

Concerning the Shanghai Composite Index, after being influenced by an external agent, its antecedent returns exert a strong pull in the initial phase, shown in Figure 5. This pull wanes rapidly, trending towards nullity post the second interval. International crude oil prices notably impact the Shanghai Composite during the initial two periods, though this influence swiftly wanes, showcasing negative trajectories in the 6th and 9th intervals. The US stock index's effects on the Shanghai Composite are palpable from periods 2 to 3 and manifest marginal downturns during the 5th and intervals 7 to 10. The influences of both on the crude oil returns are negligible post the 10th interval.



(a) (b) (c)

Fig. 5. Impulse Response Function Results (SSEC)

3.4.3 S&P 500.

In Figure 6 it is shown that, for the S&P 500, upon external stimulus, there's a tangible influence from its prior returns, Shanghai Composite returns, and international crude oil futures, peaking in the initial phase. This influence diminishes swiftly. Its inherent impact dwindles to near-zero post the subsequent period. The international crude oil futures cast a shadow, predominantly negative, on the 2nd, 5th, and 7th intervals. The Shanghai Composite's influence is generally negative but undergoes a positive transition around the 5th and 10th intervals. Both effects wane and are nearly null post the 11th interval.

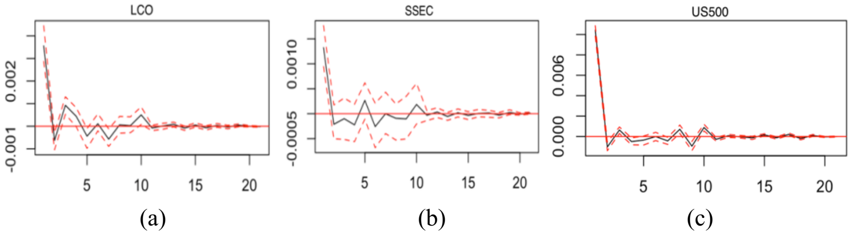


Fig. 6. Impulse Response Function Results (US500)

3.4.4 China and America stock market.

Breaking it down individually, international crude oil futures exert a near-immediate impact on both nations' stock markets, typically cresting in the inaugural period before swiftly waning. Conversely, when observing the two stock markets' influence on international crude oil futures, there's a noticeable delay: the US stock market's influence climaxes during the 6th period, while the Chinese stock market's positive thrust peaks in the 7th. Viewed through the lens of financial markets, this could be attributed to stock investors' attuned responsiveness to international crude oil futures pricing dynamics. On occasions, shifts in these futures prices could predicate recalibrated investment strategies. The futures market, in responding to stock market fluctuations, exhibits a temporal lag. This is possibly because stock markets can only obliquely dictate facets like crude oil production, transportation, and storage, thereby influencing its price points.

Additionally, when scrutinizing the reciprocal impacts between the Chinese and US stock markets, different patterns emerge. The US stock market's influence on its Chinese counterpart reached its zenith in the 2nd period. In contrast, China's influence on the US market is immediate, peaking in the very first period. Such rapid reciprocation underscores the fact that, within the interconnected global economy, stock market investors in both nations are highly attuned to foreign market intel. They are substantially swayed by international stock markets when charting investment routes. On balance, the Chinese stock market appears more malleable to US stock market movements, albeit with a slight delay. This temporal shift, in a financial context, might be rooted in the nuances of information conveyance and the idiosyncrasies inherent to the Chinese stock market.

4 Conclusion

This research delves into the interrelations among international crude oil futures returns, the Shanghai Composite Index, and the S&P 500 Index. The interaction and chain reaction triggered by shifts in returns are analyzed by impulse response analysis using the VAR model. An empirical assessment of 2954 data sets, spanning January 2011 to August 2023, led to the following conclusions.

International crude oil futures, the Chinese stock market, and the US stock market are intricately connected. The futures market swiftly impacts stock markets, overshadowing the reverse influence. Following a 10-period disruption, all three entities return to their baseline states. A rise in crude oil futures momentarily elevates both stock markets, while an uptrend in either stock market initially depresses, then boosts the futures before stabilizing. Overall, crude oil futures positively influence both stock markets, but a booming stock market phase suggests a potential decline in crude oil futures.

Reference

1. Liu, Z., Tseng, H. K., Wu, J. S., & Ding, Z. (2020). Implied volatility relationships between crude oil and the US stock markets: Dynamic correlation and spillover effects. Resources Policy, 66, 101637.
2. Jiang, Z., & Yoon, S. M. (2020). Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. Energy Economics, 90, 104835.
3. Sims C. A. (1980). Macroeconomics and reality. Econometrica: journal of the Econometric Society, 1-48.
4. Shahrestani, P., & Rafei, M. (2020). The impact of oil price shocks on Tehran Stock Exchange returns: Application of the Markov switching vector autoregressive models. Resources Policy, 65, 101579.
5. Xie L.(2020). Research on the spillover effects of the international crude oil futures market on China's new energy stock market (Master 's thesis, Chongqing Technology and Business University). https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202002&filename=1020817729.nh
6. Chen S, & Hao Y.(2021). The correlation analysis between China 's crude oil futures price and stock price index. Securities & Futures of China (02),36-55. doi: 10. 19766/ j. cnki.zgzqqh.2021.2.004.
7. Li Y. (2022). Research on China's crude oil futures price discovery and volatility spillover effect (Master's thesis, Nanjing University of Science & Technology). https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFDTEMP&filename=1023560634.nh.
8. Harris R. I. (1992). Testing for unit roots using the augmented Dickey-Fuller test: Some issues relating to the size, power and the lag structure of the test. Economics Letters, 38(4), 381-386.
9. Lütkepohl H., & Poskitt, D. S. (1991). Estimating orthogonal impulse responses via vector autoregressive models. Econometric Theory, 7(4), 487-496.
10. Inoue, A., & Kilian, L. (2013). Inference on impulse response functions in structural VAR models. Journal of Econometrics, 177(1), 1-13.