Hindawi
Journal of Mathematics
Volume 2021, Article ID 6270525, 7 pages
https://doi.org/10.1155/2021/6270525

Research Article

An Empirical Analysis of Oil and Stock Markets' Volatility Based on the DGC-MSV-t Model

Jing Zhang,[1] **Ya-Ming Zhuang**,[2] **and Jia-Bao Liu**[3]

[1]*School of Finance, Anhui University of Finance and Economics, Bengbu, Anhui, China*
[2]*School of Economics and Management, Southeast University, Nanjing, Jiangsu, China*
[3]*School of Mathematics and Physics, Anhui Jianzhu University, Hefei 230601, China*

Correspondence should be addressed to Jing Zhang; zhangjingseuc@163.com

Received 8 November 2021; Revised 13 December 2021; Accepted 17 December 2021; Published 31 December 2021

Academic Editor: Miaochao Chen

We investigate the spillover effect between crude oil future prices, crude oil spot prices, and stock index by using the multivariate stochastic volatility model. These tests between each market show the significant Granger causes of spillover effect. More and more evidences show that the crude oil price has been affected by other financial markets. The oil future played an important role in the energy market. WTI and Brent oil future have more spillover effect than INE oil future. The result shows that S&P stock market is more sensitive to the oil price than Shanghai stock market. The cross-market spillover effect we found can give some advices for the investor of oil and stock market. DIC test shows that DGC-MSV-t is considered effective and more accurate.

1. Introduction

Crude oil is the blood of modern industry and the most financialized energy product. According to the report of CNPC, China's oil dependence on foreign sources reached 70.8%, with an increase of 1.2 percentage per year. It is expected that China's oil demand will continue to rise in the future, and its dependence on foreign sources will remain high for a long time. In addition, the report also believes that the United States has achieved energy independence through the development of domestic shale gas oilfields, and its control and influence on the global oil market are increasing. OPEC's oil market share and influence are constantly being squeezed and keep going down. There are many unexpected factors in the crude oil price including geopolitical factors [1, 2]. WTI and Brent Crude Oil Futures are the most important pricing benchmarks for the US and European oil markets. In 2018, Shanghai International Energy Exchange (INE) established the first Chinese crude oil future trading product. After two years, the INE has surpassed the Oman and became the world's third largest oil future product. Crude oil prices are highly related to the national economy [3, 4]. A lot of research studies show that spillover effect and co-movement between stock and oil price exist in both developed market and emerging market [5, 6]. Chen [7] has given sufficient evidence to prove US market has one-way spillover effect to China market due to the closed economic and trading relations. The commodity future market are highly corrlated [8], spillover effect still exists even in the Bitcoin market [9].

The three oil crises in history have proved that the oil trading market is extremely vulnerable to emergencies, such as wars, terrorist attacks, and diseases. Clean energy also brings more spillover to the crude oil price [10]. Luo and Qin [11] have proved the oil price has a significant spillover to the Chinese stock index. In addition, Boubaker and Raza [12] have found that all BRICS stock markets have spillover or subspillover from oil price. The oil-importing and oil-exporting countries are both affected by the spillover of cross market [13–15]. A lot of work has been carried out using the OVX index to find the volatility spillover of different markets [16, 17]. Risk diversification and hedging need to clarify the relationship between markets [18]. Especially in 2020, the spot oil price and oil future are crashing in the COVID-19 pandemic [19]. The stochastic volatility model has added uncertain random disturbance into the time series. The

Monte Carlo method is used to estimate the random factors [20], and the degree of random disturbance is estimated on the basis of fitting historical time series [21]. The volatility models of time series mainly include GARCH [22] and SV models [23]. MSV model is effective and performs better [24]. The time-series problem can be solved by the SV model and the MCMC method [25, 26]. Various SV models have been built to solve different problems. Ghosh et al. [27] add the nonlinear method to solve nonlinear SV problem, and Nugroho and Morimoto [28] add mean equation to solve mean-SV problem. Chib et al. [29] have improved the SV model with leverage. Omori et al. [30] and Zhongxian et al. [31] have changed the N-distribution to T-distribution, which is suitable for some problems. Jacobs and Li [32] have improved the simulation method of two-factor simulation. Based on the multivariate stochastic volatility model, this paper introduces dynamic correlation coefficients, t-distribution, and Granger causality to construct models. Using the Monte Carlo method, we try to find the volatility spillover effect among INE crude oil futures' price and Shengli oilfield spot price of China, WTI crude oil futures and spot price of USA, BRENT crude oil futures and spot price of UK, the Shanghai Stock Index, and the S&P Index.

The article consists of four sections. Section 2 introduces the DGC-MSV-t model, MCMC method, and Gibbs sampling. Section 3 is empirical analysis and result of the data of stock indexes, oil spot price, and oil future price. Section 4 is the conclusion of this paper.

2. Multivariate Stochastic Volatility Model

2.1. Stochastic Volatility Model.

$$
\begin{aligned}
y_t &= \exp\left(\frac{q_t}{2}\right)\epsilon_t, \epsilon_t \overset{iid}{\sim} N\left(0, \Sigma_{\epsilon,t}\right),\\
q_{t+1} &= \mu + \psi_1\left(q_t - \mu\right) + \xi_t, \xi_t \overset{iid}{\sim} N\left(0, \sigma^2\right),
\end{aligned}
\tag{1}
$$

where y_t represents the historical logarithmic return of crude oil and stock prices. Equation (1) shows the basic model with the known y_t and the unknown ψ_t which are unobservable variables. We combined the Ganger-MSV model and the dynamic-MSV model as Yu and Meyer [33] and replace N-distribution with T-distribution:

$$
\begin{aligned}
y_t &= \exp\left(\frac{q_t}{2}\right)\epsilon_t, \epsilon_t \overset{iid}{\sim} T\left(0, \Sigma_{\epsilon,t}, o\right), \Sigma_{\epsilon,t} = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix},\\
q_{t+1} &= \mu + \psi\left(p_t - \mu\right) + \xi_t, \xi_t \overset{iid}{\sim} N\left(0, \operatorname{diag}\left(\sigma_{\xi_a}^2, \sigma_{\xi_c}^2\right)\right),\\
r_{t+1} &= v_0 + v_{ac}\left(r_t - v_0\right) + \sigma_\rho o_t, o_t \overset{iid}{\sim} N(0,1), \rho_t = \frac{\exp\left(r_t\right) - 1}{\exp\left(r_t\right) + 1}.
\end{aligned}
\tag{2}
$$

Equation (2) has multivariate time series. Taking the WTI future (AF) and Brent future (BF) for examples, y_{af} represents the price volatility of WTI future and y_{af} represents the price volatility of Brent future $\psi = \begin{pmatrix} \psi_{afaf} & \psi_{bfaf} \\ \psi_{afbf} & \psi_{bfbf} \end{pmatrix}$. ψ_{afbf} represents the cross-market spillover from WTI future to the Brent future. ψ_{bfaf} is the opposite. ψ_{afaf} and ψ_{bfbf} represent the autocorrelation of WTI future and Brent future. ρ_t represents the dynamic correlation [33]. o reflects the degree of T-distribution. q_{t+1}, μ and ψ, and $(\mu + \psi(q_{t-1} - \mu), \operatorname{diag}(\sigma_{\xi_a}^2, \sigma_{\xi_c}^2))$ distribution are as follows:

$$
\begin{aligned}
&\theta_t \mid \mu, \psi, p_t \tilde{N}\left(\mu + \psi\left(q_t - \mu\right), \operatorname{diag}\left(\sigma_{\xi_a}^2, \sigma_{\xi_c}^2\right)\right),\\
&t = 1, 2, \ldots, n,\\
&f(t; o) = \frac{\Gamma((o+1)/2)}{\Gamma(o/2)} \sqrt{\frac{1}{o\pi}} \left(1 + \frac{t^2}{o}\right)^{-(o+1)/2},\\
&f\left(p_t \mid q_t\right) = \exp\left(-\frac{q_t}{2}\right) \frac{\Gamma((o+1)/2)}{\Gamma(o/2)} \cdot \sqrt{\frac{1}{o\pi}} \left(1 + \frac{q_t^2 \exp\left(-\epsilon_t\right)}{o}\right)^{-(o+1)/2}.
\end{aligned}
\tag{3}
$$

Therefore,

$$
\begin{aligned}
L\left(\mu, \psi, o, \epsilon_{0:n}, \operatorname{diag}\left(\sigma_{\xi_a}^2, \sigma_{\xi_c}^2\right)\right) &= \prod_{t=1}^{n} f\left(p_t \mid \epsilon_t\right)\\
&= \prod_{t=1}^{n} \sqrt{\frac{1}{o\pi}} \frac{\Gamma((o+1)/2)}{\Gamma(o/2)} \exp\left(-\frac{q_t}{2}\right) \cdot \left[1 + \frac{1}{o} p_t^2 \exp\left(-\epsilon_t\right)\right]^{-(o+1)/2}\\
&= \frac{1}{(o\pi)^{n/2}} \left(\frac{\Gamma((o+1)/2)}{\Gamma(o/2)}\right)^n \exp\left(-\frac{1}{2}\sum_{t=1}^{n} \epsilon_t\right) \cdot \prod_{t=1}^{n} \left(1 + \frac{1}{o}\exp\left(-\psi_t\right)\right)^{-(o+1)/2}.
\end{aligned}
\tag{4}
$$

Table 1: Descriptive statistics.

	CF	CS	AF	AS	BF	BS	SH	SP
Mean	0.007066	−0.016718	−0.009444	0.037478	0.053494	−0.003176	−0.013046	−0.016233
Median	0.1419	0.19485	−0.016166	0.188739	0.093134	0.069478	0.261294	0.1252
Maximum	7.6421	13.2578	5.449262	5.662818	3.375938	11.87335	11.73237	13.50267
Minimum	−6.8208	−8.233565	−5.745464	−7.801777	−3.341992	−6.449077	−6.95906	−8.724438
Std. dev.	1.774179	2.127198	1.249691	2.097212	0.874198	2.122889	1.913911	2.247643
Skewness	−0.200496	0.105674	−0.267382	−0.398778	−0.587087	0.228817	−0.096954	0.127722
Kurtosis	4.143846	8.020451	5.915742	3.584046	5.550272	5.622979	7.526002	7.496187
Jarque–Bera	24.30266	417.6704	145.3603	16.16461	130.3908	117.2713	339.4729	335.4807

Table 2: The simulation results of posterior parameters of WTI and INE future.

Node	Mean	Sd	MC error	2.50%	5.00%	10.00%	Median	97.50%	Start	Sample
μ_{cf}	0.8006	0.1831	0.007931	0.4213	0.490 2	0.5677	0.8081	1.148	10000	80002
μ_{af}	0.952	0.2646	0.01158	0.3549	0.466 5	0.5905	0.9826	1.417	10000	80002
o	12.63	4.027	0.1306	7.01	7.587	8.313	11.84	22.68	10000	80002
ψ_{cfcf}	0.744	0.1496	0.006766	0.4146	0.474 1	0.5323	0.7648	0.9679	10000	80002
ψ_{cfaf}	0.1751	0.1347	0.006321	−0.008907	0.003472	0.02068	0.1491	0.4627	10000	80002
ψ_{afaf}	0.7839	0.1458	0.006601	0.4264	0.4901	0.5743	0.8151	0.9798	10000	80002
ψ_{afcf}	0.293	0.2782	0.01318	−0.04609	−0.0207	0.01095	0.2267	1.017	10000	80002
$\sigma_{\xi_{cf}}$	0.119	0.03728	0.001669	0.06548	0.07037	0.07759	0.1122	0.2096	10000	80002
$\sigma_{\xi_{af}}$	0.1741	0.07831	0.003713	0.06718	0.07468	0.08697	0.1585	0.363	10000	80002

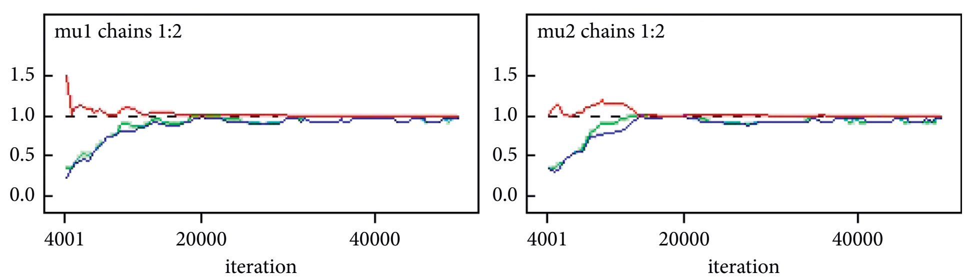

Figure 1: Gelman Rubin test results of μ_{cf} and μ_{af}.

2.2. MCMC Method and Gibbs Sampling. We use the Markov chain as follows:

$$P\{X_0 = x_0, X_1 = x_1, \ldots, X_t = x_t\} = P(X_0 = x_0)\prod_{t-1}^{t} P\left(X_i = x_i \mid X_{i-1} = x_{i-1}\right). \quad (5)$$

Therefore, the one-step transition probability is as

$$p(x_{t-1}, x_t) = P\left(X_t = x_t \mid X_{t-1} = x_{t-1}\right). \quad (6)$$

How to determine this conditional probability is a key issue. With further research, some powerful tool has been used to solve the N-P problem. Gibbs sampling set $X = (X_1, X_2)$ to follow the M-N distribution:

$$\left(\frac{x_1^{(t)}}{x_2^{(t)}}\right)\widetilde{N}\left(\begin{pmatrix} \rho^{2t-1}x_2^{(0)} \\ \rho^{2t}x_2^{(0)} \end{pmatrix}.\begin{pmatrix} 1-\rho^{4t-2} & 1-\rho^{4t-1} \\ 1-\rho^{4t-1} & 1-\rho^{4t} \end{pmatrix}\right). \quad (7)$$

3. Empirical Analysis

3.1. Data and Preprocessing. In this section, the data include INE crude oil futures (CF) and Shengli oilfield spot price (CS) of China, WTI crude oil futures (AF) and WTI crude oil spot price (AS) of USA, BRENT crude oil future (BF) and BRENT crude oil spot price (BS) of UK, the Shanghai Stock Index (SH), and the S&P Index (SP). We selected the day price from March 27, 2018, to December 31, 2019. After excluding the holidays, 8 sets of data are obtained for daily trading closing prices, each of which includes 405 common trading days. Considering the exchange rate, we obtained the logarithmic rate of return, which is abbreviated as CF, CS, AF, AS, BF, BS, SH, and SP. The data come from EIA (United States Energy Information Administration) and public database of stock market. China and USA both are the important oil importers in the world. Shengli oilfield is the largest oilfield in China and represents the spot price of China crude oil. WTI and Brent are the most important

Table 3: DIC result of CC-MSV, GC-MSV, DC-MSV, and DGC-MSV-t.

	Dbar	Dhat	pD	DIC
CC-MSV	3134.71	3089	45.712	3180.42
GC-MSV	3125.12	3081.49	43.629	3168.75
DC-MSV	3128.83	3077.95	50.88	3179.71
DGC-MSV-t	2712.07	2688.46	23.603	2735.67

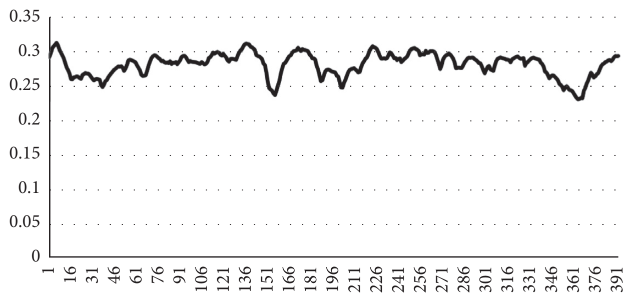

Figure 2: Dynamic correlation result.

Table 4: Volatility spillover parameter estimation result of different oil markets.

Node	Mean	2.50%	5.00%	10.00%	Median	97.50%	Is it significant?
ψ_{bfaf}	0.06004	−0.05696	−0.04283	−0.02776	0.03806	0.3061	Not significant
ψ_{afbf}	0.3032	0.09063	0.1076	0.1295	0.269	0.6695	Significant
ψ_{cfaf}	0.1751	−0.008907	0.003472	0.02068	0.1491	0.4627	Significant
ψ_{afcf}	0.293	−0.046 09	−0.0207	0.01095	0.2267	1.017	Subsignificant
ψ_{cfbf}	0.2184	−0.02287	−0.01117	0.006664	0.1973	0.5731	Subsignificant
ψ_{bfcf}	0.2808	−0.1651	−0.1231	−0.07586	0.1751	1.345	Not significant
ψ_{bsas}	0.06786	−0.04367	−0.03385	−0.021 8	0.03545	0.338	Not significant
ψ_{asbs}	0.2809	−0.006196	0.018 92	0.06708	0.2548	0.714	Significant
ψ_{csas}	0.1161	−0.02453	−0.01588	−0.005733	0.05401	0.5984	Not significant
ψ_{ascs}	0.2948	−0.01432	0.01946	0.07073	0.2718	0.7241	Significant
ψ_{csbs}	0.5694	0.056 01	0.1235	0.2235	0.5508	1.177	Significant
ψ_{bscs}	0.02523	−0.1666	−0.1376	−0.1076	0.0007	0.3682	Not significant
ψ_{bsas}	0.06786	−0.04367	−0.03385	−0.0218	0.03545	0.338	Not significant
ψ_{asbs}	0.2809	−0.006196	0.01892	0.06708	0.2548	0.714	Significant
ψ_{csas}	0.1161	−0.02453	−0.01588	−0.005733	0.05401	0.5984	Not significant
ψ_{ascs}	0.2948	−0.01432	0.01946	0.07073	0.2718	0.7241	Significant
ψ_{csbs}	0.5694	0.05601	0.1235	0.2235	0.5508	1.177	Significant
ψ_{bscs}	0.02523	−0.1666	−0.1376	−0.1076	0.0007	0.3682	Not significant

representative oil future in the world. The descriptive statistics is shown as Table 1. J-B value shows that some data are different from the normal distribution.

3.2. Parameter Estimation. Taking America WTI crude oil future (AF) and China INE crude oil future (CF) as example, we abandon the first 10,000 iterations. Then, we simulate the last 80,000 iterations to get the result as Table 2.

In Table 2, ψ_{cfaf} represents the volatility spillover from WTI future to INE future. As proposed by [33], if ψ is greater than 0 means significant spillover effect exists. The 2.5% quantile of ψ_{cfaf} is less than 0, but 5% quantile is greater than 0, which means the spillover from WTI to INE is significant in 95% confidence interval. The 5% quantile of ψ_{afcf} is less than 0 and the 5% quantile of ψ_{afcf} is greater than 0. Within 90% confidence interval which is greater than 0, we classify the spillover of ψ_{afcf} as subsignificant. The volatility level parameter μ_{cf} of INE future is 0.800 6. And μ_{af} of WTI future is 0.952. The value of μ_{cf} is lower than μ_{af}, which means the risk of the INE future is lower than the WTI future. The volatility persistence parameter ψ_{cfcf} of INE future is 0.744 and ψ_{afaf} of WTI future is 0.783 9. The INE future volatility persistence is lower than WTI future.

Figure 1 shows the Gelman test results of μ_{cf} and μ_{af}. We can see the two Markov links are lower than 1.1, and it can be considered as convergent. μ_{cf} and μ_{af} are convergent. Other parameters' results are also convergent. In Table 3, the DIC test result shows that the DGC-MSV-t model is better than other models. Dbar reflects the difference between the

Table 5: Volatility spillover parameter estimation result between oil future and spot price.

Node	Mean	2.50%	5.00%	10.00%	Median	97.50%	Is it significant?
ψ_{afas}	0.4485	0.06548	0.1181	0.1959	0.4506	0.8539	Significant
ψ_{asaf}	0.3667	0.02885	0.05408	0.09264	0.343	0.8193	Significant
ψ_{bfbs}	0.2449	−0.01832	0.001284	0.02926	0.2137	0.684	Significant
ψ_{bsbf}	0.165	−0.04118	−0.02714	−0.009801	0.1151	0.6209	Not significant
ψ_{cfcs}	0.1284	−0.0179	−0.00060	0.01764	0.115	0.3511	Subsignificant
ψ_{cscf}	0.2022	−0.05455	−0.03521	−0.01147	0.1325	0.7939	Not significant
ψ_{afbs}	0.2507	−0.006017	0.009745	0.03747	0.2138	0.7771	Significant
ψ_{bsaf}	0.146 5	−0.032 99	−0.02004	−0.004512	0.09516	0.5993	Not significant
ψ_{afcs}	0.2146	−0.09007	−0.05445	−0.01726	0.1716	0.8721	Not significant
ψ_{csaf}	0.2803	−0.01483	−0.003936	0.0127	0.2675	0.752	Subsignificant
ψ_{asbf}	0.3341	−0.03156	0.005658	0.07648	0.3116	0.8012	Significant
ψ_{bfas}	0.1218	−0.05055	−0.038	−0.02302	0.04944	0.7169	Not significant
ψ_{bfcs}	0.3971	−0.1292	−0.06635	0.01752	0.3887	1.007	Subsignificant
ψ_{csbf}	0.123	−0.04957	−0.03826	−0.02398	0.04434	0.5781	Not significant
ψ_{cfas}	0.1329	−0.07335	−0.04068	−0.01327	0.09873	0.4624	Not significant
ψ_{ascf}	0.1128	−1.097	−0.9743	−0.6685	0.1165	1.032	Not significant
ψ_{cfbs}	0.09382	−0.1008	−0.07042	−0.03843	0.07099	0.3969	Not significant
ψ_{bscf}	0.2786	−0.07741	−0.04265	−0.002324	0.2168	1.005	Not significant

Table 6: Volatility spillover parameter estimation result between stock and oil.

Node	Mean	2.50%	5.00%	10.00%	Median	97.50%	Is it significant?
ψ_{shsp}	−0.1318	−0.4226	−0.3245	−0.2498	−0.1032	−0.01694	Not significant
ψ_{spsh}	−0.02373	−0.1954	−0.1397	−0.09121	−0.006921	0.04063	Not significant
ψ_{afsp}	0.05652	−0.02654	−0.01916	−0.01082	0.03843	0.2475	Not significant
ψ_{spaf}	0.3715	−0.02974	−0.01122	0.01784	0.324	1.173	Subsignificant
ψ_{afsh}	−0.05138	−0.3714	−0.2847	−0.1895	−0.01123	0.05214	Not significant
ψ_{shaf}	−0.1472	−0.5502	−0.4185	−0.3101	−0.1049	−0.01055	Not significant
ψ_{bfsp}	0.05872	−0.03439	−0.02437	−0.01381	0.03786	0.2752	Not significant
ψ_{spbf}	0.3538	−0.02979	−0.006206	0.03227	0.3018	1.001	Subsignificant
ψ_{bfsh}	−0.004162	−0.1421	−0.09803	−0.0594	0.009145	0.05486	Not significant
ψ_{shbf}	−0.08078	−0.2779	−0.1979	−0.1532	−0.0599	−0.0182	Not significant
ψ_{cfsp}	0.0219	−0.02526	−0.01954	−0.012 96	0.01366	0.1205	Not significant
ψ_{spcf}	0.7218	0.1442	0.2036	0.2771	0.6426	1.903	Significant
ψ_{cfsh}	0.01713	−0.03673	−0.01401	−0.002724	0.0186	0.05428	Not significant
ψ_{shcf}	−0.07241	−0.1865	−0.1588	−0.1307	−0.06423	−0.00017	Not significant
ψ_{assp}	0.06211	−0.0332	−0.02422	−0.0132	0.04344	0.2481	Not significant
ψ_{spas}	0.3739	−0.019 26	0.006416	0.04224	0.3251	1.103	Subsignificant
ψ_{assh}	−0.00164	−0.1386	−0.09633	−0.05549	0.008464	0.06549	Not significant
ψ_{shas}	−0.04689	−0.1528	−0.1152	−0.08902	−0.03852	0.001158	Not significant
ψ_{bssp}	0.07731	−0.01021	−0.001435	0.01242	0.0677	0.218	Subsignificant
ψ_{spbs}	0.2014	−0.09414	−0.07542	−0.05464	0.055 58	1.115	Not significant
ψ_{bssh}	−0.02373	−0.1954	−0.1397	−0.09121	−0.006921	0.04063	Not significant
ψ_{shbs}	−0.1318	−0.4226	−0.3245	−0.2498	−0.1032	−0.01694	Not significant
ψ_{cssp}	0.03079	−0.03393	−0.0264	−0.01759	0.02132	0.1511	Not significant
ψ_{spcs}	0.4105	0.05969	0.1216	0.171	0.3671	0.9767	Significant
ψ_{cssh}	0.03438	0.003004	0.007927	0.01285	0.03056	0.08961	Significant
ψ_{shcs}	−0.01635	−0.06732	−0.05935	−0.04977	−0.01684	0.04631	Not significant

model and the actual data, the smaller the better. pD reflects the complexity of the model; the larger the value, the more complicated. Dbar and pD jointly determine the DIC test value. The total DIC score is the lowest in the DGC-t-MSV model. Considering the adaptability and complexity comprehensively, it can be seen that the DGC-t-MSV model is the most suitable model for testing the volatility spillover. Figure 2 shows the dynamic correlation result between America WTI crude oil future (AF) and China INE crude oil future (CF).

In Table 4, we can see all the spillover from each oil futures to others. ψ_{bfaf}, ψ_{bfcf}, ψ_{bsas}, ψ_{bsas}, ψ_{csas}, ψ_{bscs}, ψ_{bsas}, ψ_{csas}, and ψ_{bscs} in 90% confidence are lower than zero. Brent oil future has significant one-way spillover to WTI oil future. WTI future has higher spillover to INE future. Also, we can see all the spillover between spot oil prices. The Brent oil spot price has one-way spillover effect to WTI and Shengli oilfield spot price. Unexpected, Shengli oilfield spot price has one-way spillover to WTI spot price. Using the same method, we can get the relationship of spillover between oil future and spot price in Table 4. It shows that WTI spot price and future price has significant two-way spillover effect. In Table 5, the Brent spot price has one-way spillover effect to Brent future and WTI future. Brent future has spillover to the price of WTI spot price. Shengli oilfield spot price has a subsignificant one-way spillover to Brent future. Three crude oil spot prices have volatility spillover to INE futures. Table 6 shows the spillover estimation result between stock and oil. There only exist a few spillover relations between the stock market and the oil market. The spillover from WTI, Brent, and INE oil future to the stock market of S&P exists. However, the Shanghai stock index has a significant one-way spillover to the Shengli oilfield spot price.

4. Conclusion

The cross-market spillover effect we found can give some advice to correctly diversify investment and reduce risks. (1) The empirical results show that WTI and Brent oil future have more spillover to both spot price and future price. The oil future played an important role in the energy market and economic. INE oil future is a fast-growing product of China. However, INE oil future still lacks international influence. (2) S&P stock market is more sensitive to the oil price than Shanghai stock market. After experiencing three oil crises, the investors of USA fully understand the impact of crude oil prices on the market. The investor in China does not pay attention to the volatility of crude oil price. S&P includes many oil company, which is not included in the Shanghai stock market. (3) The volatility of the Chinese and American stock markets is not highly correlated and suitable for diversified investment. DIC test shows that DGC-MSV-t is considered effective and more accurate. Our possible future studies will be focus on the difference when market volatility increases and decreases based on regime-switching method of stochastic volatility.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

All authors contributed to this paper equally. Jing Zhang conceptualized the study, developed the methodology, helped with software, visualized the study, and wrote and prepared the original draft. Ya-ming Zhuang curated the data and reviewed and edited the manuscript. Jia-Bao Liu investigated and supervised the study.

Acknowledgments

This work was supported by the Major Projects of Social Sciences in Anhui Universities (SK2020ZD006), the General Project of Anhui Natural Science Foundation (1908085MG232), and the Doctoral research fund of Anhui University of Finance and Economics (85051).

References

[1] S. Y. Choi and C. Hong, "Relationship between uncertainty in the oil and stock markets before and after the shale gas revolution: evidence from the ovx, vix, and vkospi volatility indices," *PLoS One*, vol. 15, Article ID e0232508, 2020.

[2] J. Zhang, J.-B. Liu, M. K. Siddiqui, and W. Nazeer, "Energy and economic aspects of synthesis gas production from oil sludge and plastic waste," *Petroleum Science and Technology*, vol. 37, no. 4, pp. 430–435, 2019.

[3] S. Nazlioglu, C. Erdem, and U. Soytas, "Volatility spillover between oil and agricultural commodity markets," *Energy Economics*, vol. 36, pp. 658–665, 2013.

[4] J. Ran and J. P. Voon, "Does oil price shock affect small open economies? evidence from Hong Kong, Singapore, South Korea and Taiwan," *Applied Economics Letters*, vol. 19, no. 16, pp. 1599–1602, 2012.

[5] M. Basta and P. Molnar, "Oil market volatility and stock market volatility," *Finance Research Letters*, vol. 26, pp. 204–214, 2018.

[6] E. Bouri, D. Lien, D. Roubaud, and S. J. H. Shahzad, "Directional predictability of implied volatility: from crude oil to developed and emerging stock markets," *Finance Research Letters*, vol. 27, pp. 65–79, 2018.

[7] W.-R. Yang and Y.-L. Chen, "The response of dynamic herd behavior to domestic and U.S. market factors: evidence from the greater China stock markets," *Emerging Markets Finance and Trade*, vol. 51, no. 1, pp. S18–S41, 2015.

[8] A. I. Maghyereh, B. Awartani, and P. Tziogkidis, "Volatility spillovers and cross-hedging between gold, oil and equities: evidence from the gulf cooperation council countries," *Energy Economics*, vol. 68, pp. 440–453, 2017.

[9] G. J. Wang, C. Xie, D. Wen, and L. Zhao, "When bitcoin meets economic policy uncertainty (epu): measuring risk spillover effect from epu to bitcoin," *Finance Research Letters*, vol. 31, 2019.

[10] A. Dutta, "Oil price uncertainty and clean energy stock returns: new evidence from crude oil volatility index," *Journal of Cleaner Production*, vol. 164, pp. 1157–1166, 2017.

[11] X. Luo and S. Qin, "Oil price uncertainty and Chinese stock returns: new evidence from the oil volatility index," *Finance Research Letters*, vol. 20, pp. 29–34, 2017.

[12] H. Boubaker and S. A. Raza, "A wavelet analysis of mean and volatility spillovers between oil and brics stock markets," *Energy Economics*, vol. 64, pp. 105–117, 2017.

[13] A. Behar and R. A. Ritz, "Opec vs. us shale: analyzing the shift to a market-share strategy," *Energy Economics*, vol. 63, pp. 185–198, 2017.

[14] J. C. Reboredo, "Modelling oil price and exchange rate comovements," *Journal of Policy Modeling*, vol. 34, no. 3, pp. 419–440, 2012.

[15] Y. Wang, C. Wu, and L. Yang, "Oil price shocks and stock market activities: evidence from oil-importing and oil-exporting countries," *Journal of Comparative Economics*, vol. 41, no. 4, pp. 1220–1239, 2013.

[16] H. Chen, L. Liu, and X. Li, "The predictive content of cboe crude oil volatility index," *Physica A: Statistical Mechanics and its Applications*, vol. 492, pp. 837–850, 2018.
[17] Y. Chen and Y. Zou, "Examination on the relationship between ovx and crude oil price with kalman filter," *Procedia Computer Science*, vol. 55, pp. 1359–1365, 2015.
[18] M. Caporin and F. Fontini, "The long-run oil-natural gas price relationship and the shale gas revolution," *Energy Economics*, vol. 64, pp. 511–519, 2017.
[19] E. Bouri, R. Demirer, R. Gupta, and C. Pierdzioch, "Infectious diseases, market uncertainty and oil market volatility," *Energies*, vol. 13, 2020.
[20] J. B. Liu and S. N. Daoud, "Number of spanning trees in the sequence of some graphs," *Complexity*, vol. 2019, Article ID 4271783, 22 pages, 2019.
[21] S. Kim, N. Shepherd, and S. Chib, "Stochastic volatility: likelihood inference and comparison with arch models," *Review of Economic Studies*, vol. 65, no. 3, pp. 361–393, 1998.
[22] T. Bollerslev, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics*, vol. 31, no. 3, pp. 307–327, 1986.
[23] R. Liesenfeld and J.-F. Richard, "Univariate and multivariate stochastic volatility models: estimation and diagnostics," *Journal of Empirical Finance*, vol. 10, no. 4, pp. 505–531, 2003.
[24] D. Chun, H. Cho, and J. Kim, "Crude oil price shocks and hedging performance: a comparison of volatility models," *Energy Economics*, vol. 81, pp. 1132–1147, 2019.
[25] M. V. Kulikova and D. R. Taylor, "Stochastic volatility models for exchange rates and their estimation using quasi-maximum-likelihood methods: an application to the South African rand," *Journal of Applied Statistics*, vol. 40, no. 3, pp. 495–507, 2013.
[26] W. Surapaitoolkorn, "Variable dimension via stochastic volatility model using FX rates," *Journal of Applied Statistics*, vol. 40, no. 10, pp. 2110–2128, 2013.
[27] H. Ghosh, B. Gurung, and Prajneshu, "Kalman filter-based modelling and forecasting of stochastic volatility with threshold," *Journal of Applied Statistics*, vol. 42, no. 3, pp. 492–507, 2015.
[28] D. B. Nugroho and T. Morimoto, "Box-cox realized asymmetric stochastic volatility models with generalized student'st-error distributions," *Journal of Applied Statistics*, vol. 43, no. 10, pp. 1906–1927, 2016.
[29] S. Chib, F. Nardari, and N. Shephard, "Analysis of high dimensional multivariate stochastic volatility models," *Journal of Econometrics*, vol. 134, no. 2, pp. 341–371, 2006.
[30] Y. Omori, S. Chib, N. Shephard, and J. Nakajima, "Stochastic volatility with leverage: fast and efficient likelihood inference," *Journal of Econometrics*, vol. 140, no. 2, pp. 425–449, 2007.
[31] M. Zhongxian, D. McLeish, A. W. Kolkiewicz, and T. S. Wirjanto, "Comparison of asymmetric stochastic volatility models under different correlation structures," *Journal of Applied Statistics*, vol. 44, pp. 1350–1368, 2017.
[32] K. Jacobs and X. Li, "Modeling the dynamics of credit spreads with stochastic volatility," *Management Science*, vol. 54, no. 6, pp. 1176–1188, 2008.
[33] J. Yu and R. Meyer, "Multivariate stochastic volatility models: Bayesian estimation and model comparison," *Econometric Reviews*, vol. 25, no. 2-3, pp. 361–384, 2006.