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Research Article

Dynamic Cross-Market Volatility Spillover Based on MSV Model: Evidence from Bitcoin, Gold, Crude Oil, and Stock Markets

Jing Zhang [1] and Qi-zhi He [2]

[1]School of Economics and Management, Southeast University, Nanjing, Jiangsu, China
[2]School of Statistics and Mathematics, Zhejiang Gongshang University, Hangzhou, Zhejiang, China

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

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This paper examines the spillover effect between bitcoin, gold, crude oil, and major stock markets by using the MSV model with dynamic correlation and Granger causality. The empirical results of the DC-GC-MSV model are logically correct and convergent. The DIC test result has proved that the DC-GC-MSV model is better and more accurate. Bitcoin has no significant Granger causality spillover effect than other assets. As a safe haven product for stock assets, gold price has one-way spillover effect from stock market volatility. Moreover, crude oil has the highest correlation with the stock market. In the recent COVID-19 epidemic and the sluggish economic environment, investors need to consider a balanced asset allocation among low-correlation assets, medium-correlation assets, and high-correlation assets to reduce risks.

1. Introduction

Bitcoin has been around for a short time, but its influence is increasing day by day. It is generally believed that there is a certain degree of connection between the commodity market and the stock market. After 10 years of development, bitcoin has gradually been regarded as an investment product similar to gold. Its ability to maintain value and diversify risks has received increasing attention. Early research believes that the volatility of bitcoin is highly endogenous and speculative, just like chaos [1]. Some research studies [2, 3] have show that the volatility of seven electronic cryptocurrencies is highly random, highly chaotic, and highly risky, so they cannot be considered suitable for hedging purposes. Although the academic research on bitcoin theory and models has just begun, and bitcoin has become a practical financial product. Especially after the Chicago Board of Trade (CME Group) launched bitcoin futures products, bitcoin can be legally traded and the transaction data was standardized. It provides a foundation for the further research on volatility spillover of bitcoin. The uncertainty of global economy provides the possibility that the bitcoin becomes a new basket for diversified investment [4]. Some researchers [5–7] have studied the asymmetry, thick tail, long-term, and short-term features of bitcoin price volatility. The cryptocurrencies usually have thick tails, autocorrelation, and asymmetry [8]. It brings the cryptocurrency closer to the general financial product such as oil future or gold [9].

Gold has long been considered as a safe haven for hedging stocks. But more and more studies have put forward different views. Wen and Cheng [10] believe that gold can be used as a safe asset in emerging markets such as Thailand. In contrast, the US dollar has better risk reduction capabilities. Choudhry et al. [11] have used a multivariate nonlinear dynamic test to prove that gold has a close relationship with stock market volatility and cannot be used to lower the risk in stock market. Hussain Shahzad et al. [12] have found that compared with the bond market, the gold market cannot be used as a hedging tool for the stock market. Gold needs some qualifications related to market conditions before it can be used as a tool to hedge the risk of other assets [12, 13]. For example, only when stocks and gold are in extremely low volatility or high volatility periods, gold can be used as a hedging tool for diversified investment [14].

Spillover effect often occurs between different assets in developing and developed market [15]. Many studies show that diversification of different assets with lower correlation is an important way of hedging [16–18]. Cryptocurrencies also have spillover effect [19]. In 2020, COVID-19 has hit the oil price and caused the stock market panic. The investors and researchers try to find a new basket to diversify risks [20].

GARCH [21] and SV models [22] are often used to detect the volatility of price. The MSV model has been proved efficient and accurate in many situations [23]. The NP problem of multivariate stochastic volatility model can be solved by the Markov Monte Carlo method [24, 25]. Many SV models have been established to solve different problems, such as nonlinear [26], mean [27], leverage [28], T-distribution [29], and two-factor [30]. This paper has established a multivariate stochastic volatility model with dynamic correlation and Granger causality test between each series. We have simulated the volatility spillover between each asset through the Markov Monte Carlo method, and we provide advice on diversified investment in bitcoin, gold, crude oil, and stock assets.

2. Multivariate Stochastic Volatility Model

2.1. Stochastic Volatility Model

2.1.1. Basic MSV Model.

$$
\begin{aligned}
y_t &= \operatorname{diag}\left(\exp\left(\frac{q_t}{2}\right)\right)\varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0, I),\\
q_{t+1} &= \mu + \operatorname{diag}(\phi_{11}, \phi_{22})(q_t - \mu) + \xi_t, \xi_t \overset{iid}{\sim} N\left(0, \operatorname{diag}\left(\sigma^2_{\xi_1}, \sigma^2_{\xi_2}\right)\right).
\end{aligned}
\tag{1}
$$

In equation (1), y_t is the yield sequence. ϕ_{11} and ϕ_{22} are unobserved. y_t represents the yield at time t. ε_t represents the volatility of yield sequence. ξ_t represents the independent disturbance of yield sequence volatility. σ represents the standard error. ϕ_{11} and ϕ_{22} are the continuous parameters of yield sequence.

2.1.2. GC-MSV Model.

$$
\begin{aligned}
y_t &= \operatorname{diag}\left(\exp\left(\frac{q_t}{2}\right)\right)\varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0, I),\\
q_{t+1} &= \mu + \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}(q_t - \mu) + \xi_t, \xi_t \overset{iid}{\sim} N\left(0, \operatorname{diag}\left(\sigma^2_{\xi_1}, \sigma^2_{\xi_2}\right)\right).
\end{aligned}
\tag{2}
$$

In equation (2), Yu [31] has added one-way Granger cause test in the MSV model for the first time. Equation (2) has an improved two-way Granger cause test in the MSV model. When ϕ_{12} and ϕ_{21} are nonzero, a Granger causality in volatility between the two sequence is obvious. ϕ_{12} represents the Granger cause of sequence 1 from sequence 2. It suggests that the volatility in sequence 2 Granger causes the volatility in sequence 1. ϕ_{12} represents the opposite. ϕ_{11} and ϕ_{22} represent the autocorrelation of sequence 1 and sequence 2.

2.1.3. DC-MSV Model.

$$
\begin{aligned}
p_t &= \operatorname{diag}\left(\exp\left(\frac{q_t}{2}\right)\right)\varepsilon_t, \varepsilon_t \overset{iid}{\sim} T\left(0, \Sigma_{\varepsilon,t}, o\right),\\
\sum_{\varepsilon,t} &= \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix},\\
q_{t+1} &= \mu + \operatorname{diag}(\phi_{11}, \phi_{22})(p_t - \mu) + \xi_t, \xi_t \overset{iid}{\sim} N\left(0, \operatorname{diag}\left(\sigma^2_{\xi_{cf}}, \sigma^2_{\xi_{af}}\right)\right),\\
r_{t+1} &= v_0 + v_{ac}(r_t - v_0) + \sigma_\rho o_t, o_t \overset{iid}{\sim} N(0,1), \rho_t = \frac{\exp(r_t) - 1}{\exp(r_t) + 1}.
\end{aligned}
\tag{3}
$$

In equation (3), ρ_t reflects the time-varying dynamic correlation, ranging from −1 to 1. Yu [31] has achieved the constraint by using the Fisher transformation, following the suggestion of Tsay [32] in the MARCH model.

2.1.4. DC-GC-MSV Model.

$$
\begin{aligned}
p_t &= \operatorname{diag}\left(\exp\left(\frac{q_t}{2}\right)\right)\varepsilon_t, \varepsilon_t \overset{ii\,d}{\sim} T\left(0, \Sigma_{\varepsilon,t}, o\right),\\
\sum_{\varepsilon,t} &= \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix},\\
q_{t+1} &= \mu + \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}\left(p_t - \mu\right) + \xi_t, \xi_t \overset{ii\,d}{\sim} N\left(0, \operatorname{diag}\left(\sigma^2_{\xi_{cf}}, \sigma^2_{\xi_{af}}\right)\right),\\
r_{t+1} &= v_0 + v_{ac}\left(r_t - v_0\right) + \sigma_\rho o_t, o_t \overset{ii\,d}{\sim} N(0,1), \rho_t = \frac{\exp\left(r_t\right) - 1}{\exp\left(r_t\right) + 1}.
\end{aligned}
\tag{4}
$$

In equation (4), we have used the DC-MSV and GC-MSV model to improve the multivariate stochastic volatility model. The DC-GC-MSV model has the time-varying dynamic correlation and the Granger causality test. When ϕ_{12} and ϕ_{21} are nonzero, the Granger causality in volatility between the two sequence is obvious. ϕ_{12} represents the Granger cause of sequence 1 from sequence 2. It suggests that the volatility in sequence 2 Granger causes the volatility in sequence 1. ϕ_{12} represents the opposite. ϕ_{11} and ϕ_{22} represent the autocorrelation of sequence 1 and sequence 2. ρ_t reflects the time varying dynamic correlation, ranging from −1 to 1.

2.2. Markov Monte Carlo Method and Gibbs Sampling. The Markov Monte Carlo method assumes that $\{X_t, t \in T\}$ is a random process with a discrete set $I = \{x_1, x_2, \ldots\}$ as follows:

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

Therefore, we determine the transition probability by its one-step probability:

$$
\begin{aligned}
p\left(x_{t-1}, x_t\right) &= P\left(X_t = x_t | X_{t-1} = x_{t-1}\right),\\
p\left(x, x'\right) &= \pi\left(x_1 | x_2, \ldots, x_n\right)\pi\left(x_2 | x_1', \ldots, x_n\right)\ldots\pi\left(x_n | x_1', \ldots, x_{n-1}'\right).
\end{aligned}
\tag{6}
$$

Then, using Gibbs sampling as follows:

(1) Sampling $x_1^{(t)}$ from $\pi(x_1|x_2^{(t-1)}, \ldots, x_n^{(t-1)})$

(2) Sampling $x_2^{(t)}$ from $\pi(x_2|x_1^{(t)}, x_3^{(t-1)}, \ldots, x_n^{(t-1)})$

. . . . . .

(i) Sampling $x_i^{(t)}$ from $\pi(x_i|x_1^{(t)}, x_{t-1}^{(t)}, x_{i-1}^{(t-1)}, \ldots, x_n^{(t-1)})$

. . . .

(n) Sampling $x_n^{(t)}$ from $\pi(x_n|x_1^{(t)}, x_2^{(t)}, \ldots, x_{n-1}^{(t)})$

$X = (X_1, X_2)$ follows a multivariate normal distribution:

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

When $t \longrightarrow \infty$, the distribution of $(x_1^{(t)}, x_2^{(t)})$ will converge.

3. Empirical Analysis

3.1. Data and Preprocessing. In this section, we choose the most important assets of cybercurrency, gold, oil future, and

Table 1: Descriptive statistics.

	BC	GD	BO	SP	DQ	NQ	SH	JP	GE	EN
Mean	0.070605	0.05471	−0.045092	0.047951	0.029011	0.09324	−0.000158	0.019085	0.004953	−0.026783
Median	0.067047	0.058946	0.167839	0.149765	0.124852	0.194013	0.03062	0.055801	0.080494	0.059978
Maximum	23.63048	4.686004	19.07858	8.968316	10.76433	8.934695	7.548126	7.731375	10.41429	8.666807
Minimum	−32.14742	−6.261981	−30.98756	−12.76521	−13.84181	−13.14915	−6.712451	−6.273569	−13.05486	−11.51243
Std. dev.	5.110593	0.987517	3.355018	1.558724	1.649297	1.70769	1.321642	1.339494	1.560103	1.3618
Skewness	−0.307979	−0.580902	−1.820156	−1.187611	−1.18846	−1.096672	−0.166518	0.038317	−0.754934	−1.087716
Kurtosis	8.086177	9.426696	27.51384	18.46515	19.97004	13.69137	7.028823	8.191657	16.77241	16.43635
Jarque–Bera	692.3068	1124.952	16199.01	6456.934	7744.543	3141.686	431.0288	711.0483	5062.918	4886.44

Table 2: The simulation results of posterior parameters of bitcoin and Dow Jones.

Node	Mean	SD	MC error	2.50%	5.00%	10.00%	Median	97.50%	Start	Sample
μ_{bt}	2.497	0.1674	0.002905	2.17	2.226	2.288	2.496	2.83	10000	100001
μ_{dq}	−0.2231	0.3739	0.007361	−1.028	−0.8612	−0.6923	−0.2049	0.4772	10000	100001
ϕ_{btbt}	0.6768	0.08706	0.003041	0.4844	0.5195	0.5597	0.6857	0.8222	10000	100001
$\phi_{dq\ bt}$	0.02731	0.0439	0.000828	−0.05429	−0.04121	−0.02648	0.02541	0.1199	10000	100001
$\phi_{dq\ dq}$	0.9614	0.01504	0.000425	0.9282	0.9344	0.9414	0.9627	0.987	10000	100001
$\phi_{bt\ dq}$	0.01894	0.01935	0.000468	−0.01839	−0.0122	−0.005343	0.01875	0.05812	10000	100001
$\sigma_{\xi_{bt}}$	0.9708	0.1393	0.00529	0.7099	0.749	0.7926	0.9679	1.25	10000	100001
$\sigma_{\xi_{dq}}$	0.3275	0.04926	0.002138	0.2412	0.253	0.2672	0.3236	0.4319	10000	100001

stock index, including CME Group bitcoin futures (BC), international gold price (GD), Brent crude oil future price (BO), and 7 major stock indexes. The Chicago Mercantile Exchanges Bitcoin futures is the worlds largest bitcoin futures product, which has an important influence on the cybercurrency market in terms of market size and brand effect. S&P, Dow Jones, and Nasdaq are the major U.S. stock indexes. The Shanghai Composite Index is a major stock index in China. The Nikkei 225 is a major stock index in Japan. The DAX and the FTSE Index are important stock indexes in Europe. British Brent crude oil futures are the most important crude oil futures products and have an important influence on crude oil market prices. All asset data come from the open market data. Table 1 is the descriptive statistics result of 10 asset prices.

3.2. Parameter Estimation. In this paper, we have used the WinBUGs software to do the MCMC simulation. Taking bitcoin (BC) and Dow Jones index (DQ) as example, we burn-in the first 10,000 iterations. In Table 2, we simulate the last 100,000 iterations as follows.

In Table 2, $\phi_{dq\ bt}$ reflects the volatility of bitcoin has the Granger cause of Dow Jones stock market. $\phi_{dq\ bt}$ and $\phi_{bt\ dq}$ are nearly zero, which means the spillover effect is not obvious. μ_{bt} shows the volatility of bitcoin is 2.497, and μ_{dq} shows the volatility of Dow Jones index is −0.2231. Bitcoin volatility is obviously greater than stock market. Therefore, the cybercurrency has greater risk than stock. $\phi_{dq\ bt}$ of bitcoin is 0.6768, and $\phi_{bt\ dq}$ is 0.9614. This means Dow Jones index has more volatility persistence than bitcoin. In Figure 1, the Gelman Rubin test results are good. The result of each parameter is lower than 1.1 and convergent. The simulation results of this paper are also convergent. The deviance information criterion (DIC) is a popular method to test the MCMC simulation result. In Table 3, the DIC test results prove the DC-GC-MSV model is better than other models.

If $\phi 12$ and $\phi 12$ are significantly nonzero, it means there is a Granger causality of spillover effects between two assets [31]. We have defined $\phi 12$ and $\phi 21$ 2.5% quantile is greater than zero as positive significant. If only 5% quantile is greater than zero, it can be defined as sub-significant. Table 4 shows the spillover relation between bitcoin, gold, and oil. $\phi_{bog\ d}$ of oil price is positive which means one-way spillover to the gold price. Table 5 shows the spillover relation between bitcoin and stock index. There is no significant spillover. Table 6 shows the spillover relation between gold and stock. $\phi_{spg\ d}$, $\phi_{dq\ g\ d}$, $\phi_{nqg\ d}$, $\phi_{jpg\ d}$, $\phi_{geg\ d}$, and $\phi_{eng\ d}$ are positive. The result reflects a significant one-way spillover from stock to gold. Table 7 shows the spillover relation between oil and stock index. The index of S&P, Dow Jones, NASDAQ, and FTSE have two-way spillover to oil price. The Brent oil future price causes the one-way spillover to ϕ_{bojp} because Japan is highly dependent on crude oil. As an emerging stock market, the Chinese stock market did not reflect a significant spillover to bitcoin, gold, and oil.

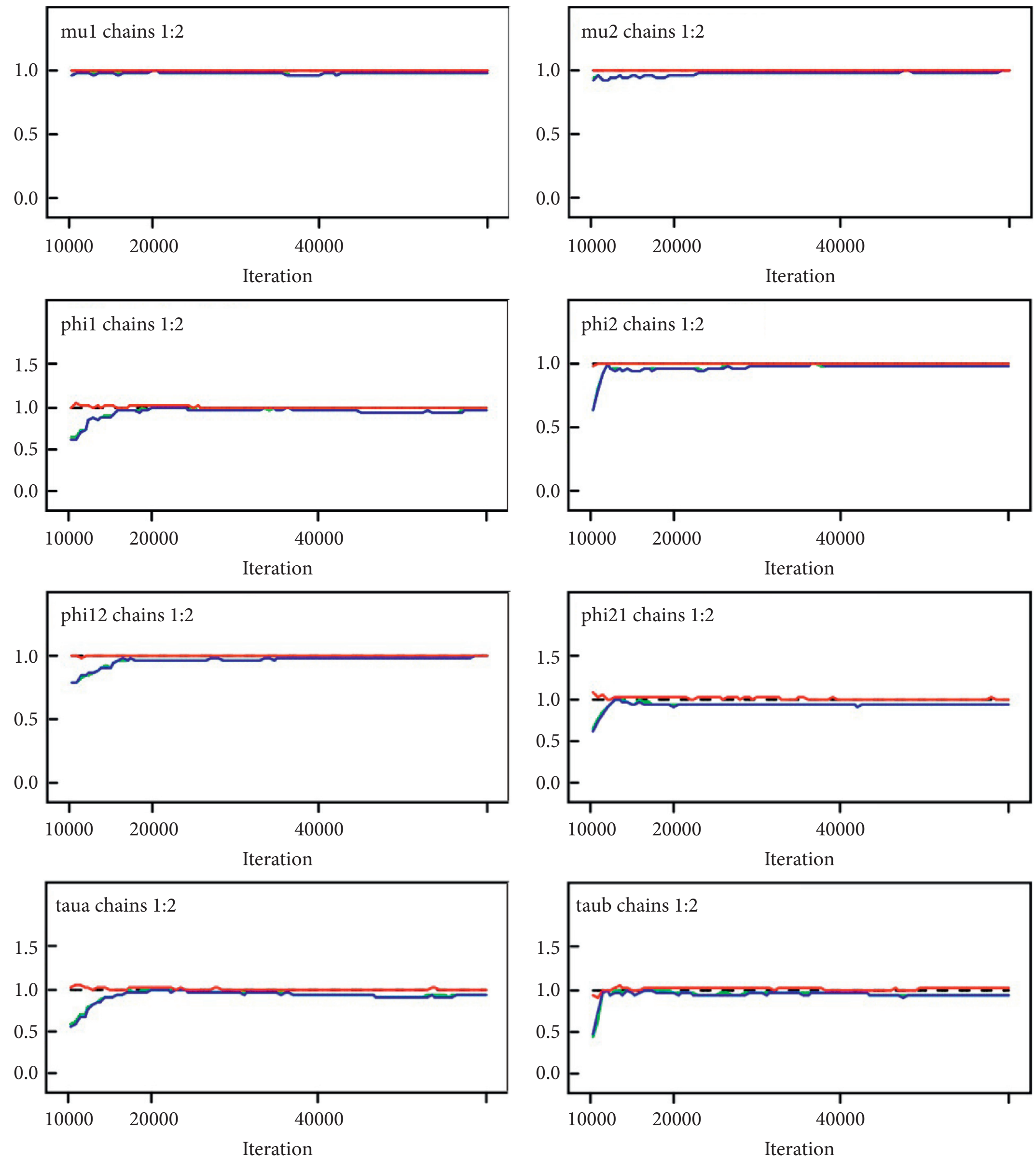

Figure 1: Gelman Rubin test results.

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

	Dbar	Dhat	pD	DIC
CC-MSV	5122.68	4898.25	224.429	5347.11
GC-MSV	5125.5	4902.97	222.528	5348.02
DC-MSV	5098.34	4871.57	226.765	5325.1
DC-GC-MSV	5089.59	4857.83	231.761	5321.35

Table 4: Granger causality result between bitcoin, gold, and oil.

Node	Mean	SD	MC error	2.50%	5.00%	10.00%	Median	97.50%	is it significant
ϕ_{bobt}	0.09138	0.05804	0.00147	−0.0101	0.004241	0.02116	0.0871	0.2177	Not significant
ϕ_{btbo}	0.007311	0.02083	0.00054	−0.03462	−0.02706	-0.01888	0.007523	0.04801	Not significant
$\phi_{g\ db\ t}$	0.07217	0.07689	0.00188	−0.06467	−0.04413	−0.02024	0.06662	0.2394	Not significant
$\phi_{btg\ d}$	0.02778	0.02933	0.00078	−0.02335	−0.01526	−0.006421	0.02506	0.09253	Not significant
$\phi_{bog\ d}$	0.09208	0.049	0.00189	0.0198	0.02779	0.03782	0.08427	0.2093	Significant
$\phi_{g\ db\ o}$	0.03736	0.03113	0.00097	−0.01791	−0.00913	7.33E-04	0.03491	0.1062	Not significant

Table 5: Granger causality result between bitcoin and stock index.

Node	Mean	SD	MC error	2.50%	5.00%	10.00%	Median	97.50%	is it significant
ϕ_{spbt}	0.0333	0.04531	0.00093	−0.04887	−0.03595	−0.02179	0.03073	0.1307	Not significant
ϕ_{btsp}	0.01852	0.01969	0.00047	−0.02023	−0.01362	−0.006269	0.01845	0.05747	Not significant
$\phi_{dq\ bt}$	0.02731	0.0439	0.00083	−0.05429	−0.04121	−0.02648	0.02541	0.1199	Not significant
$\phi_{bt\ dq}$	0.01894	0.01935	0.00047	−0.01839	−0.0122	−0.005343	0.01875	0.05812	Not significant
ϕ_{nqbt}	0.0392	0.05164	0.00111	−0.0547	−0.04006	−0.02341	0.03619	0.1494	Not significant
ϕ_{btnq}	0.01018	0.01866	0.00046	−0.02656	−0.0203	−0.01332	0.01007	0.04773	Not significant
ϕ_{shbt}	−0.06547	0.08955	0.00237	−0.2596	−0.2204	−0.1788	−0.05989	0.09509	Not significant
ϕ_{btsh}	-0.0164	0.02621	0.00065	−0.07173	-0.06052	−0.04901	−0.01551	0.03298	Not significant
ϕ_{jpbt}	0.0359	0.07372	0.00186	−0.09611	−0.07636	−0.05302	0.03112	0.1961	Not significant
ϕ_{btjp}	0.01646	0.01802	0.00051	−0.01713	-0.01162	−0.005288	0.01568	0.05464	Not significant
ϕ_{gebt}	0.04422	0.06016	0.00145	−0.06457	-0.04782	-0.0285	0.04071	0.1735	Not significant
ϕ_{btge}	0.02146	0.02013	0.00054	−0.01625	−0.01018	−0.00316	0.02068	0.06322	Not significant
ϕ_{enbt}	0.0082	0.05472	0.00119	−0.09453	-0.07761	−0.05864	0.006091	0.1233	Not significant
ϕ_{bten}	0.02341	0.01784	0.00041	−0.01174	−0.005739	0.001106	0.02335	0.05894	Not significant

Table 6: Granger causality result between gold and stock index.

Node	Mean	SD	MC error	2.50%	5.00%	10.00%	Median	97.50%	is it significant
$\phi_{spg\ d}$	0.09419	0.04693	0.00181	0.02231	0.03025	0.04032	0.08754	0.204	Significant
$\phi_{g\ ds\ p}$	0.04243	0.03532	0.00115	−0.02026	−0.01088	−1.39E-04	0.03992	0.1196	Not significant
$\phi_{dq\ g\ d}$	0.1075	0.05273	0.00210	0.02767	0.03588	0.04673	0.1004	0.2316	Significant
$\phi_{g\ dd\ q}$	0.02677	0.03328	0.00095	−0.03251	−0.02359	−0.01318	0.02448	0.09864	Not significant
$\phi_{nqg\ d}$	0.1286	0.06646	0.00274	0.03335	0.04298	0.05513	0.1167	0.2915	Significant
$\phi_{g\ dn\ q}$	0.04202	0.03985	0.00142	−0.02514	−0.01551	−0.004593	0.03834	0.1302	Not significant
$\phi_{shg\ d}$	0.03269	0.03447	0.00096	−0.03706	−0.02348	−0.009221	0.0326	0.1026	Not significant
$\phi_{g\ ds\ h}$	−0.02941	0.02648	0.00067	−0.08281	−0.0725	-0.06166	−0.02944	0.02366	Not significant
$\phi_{jpg\ d}$	0.09206	0.05971	0.00248	0.002851	0.01263	0.02488	0.08283	0.2343	Significant
$\phi_{g\ dj\ p}$	0.02522	0.03162	0.00124	−0.02382	−0.0173	−0.009797	0.02056	0.09874	Not significant
$\phi_{geg\ d}$	0.1734	0.09629	0.00436	0.04157	0.05399	0.07054	0.1534	0.4118	Significant
$\phi_{g\ dg\ e}$	0.04525	0.04387	0.00163	−0.02623	−0.0163	−0.005077	0.03986	0.1469	Not significant
$\phi_{eng\ d}$	0.2194	0.09351	0.00396	0.07583	0.09148	0.1126	0.2058	0.4397	Significant
$\phi_{g\ de\ n}$	0.04403	0.04538	0.00163	−0.03077	−0.02058	−0.008529	0.0391	0.1466	Not significant

Table 7: Granger causality result between oil and stock index.

Node	Mean	SD	MC error	2.50%	5.00%	10.00%	Median	97.50%	is it significant
ϕ_{spbo}	0.2311	0.1148	0.00527	0.07038	0.08623	0.106	0.208	0.5111	Significant
ϕ_{bosp}	0.06949	0.04401	0.00160	−0.002345	0.006382	0.0174	0.06467	0.1691	Subsignificant
$\phi_{dq\ bo}$	0.3681	0.1406	0.00612	0.1179	0.1464	0.1864	0.3638	0.6645	Significant
$\phi_{bo\ dq}$	0.1216	0.07619	0.00327	0.004598	0.01845	0.03468	0.1107	0.3041	Significant
ϕ_{nqbo}	0.1664	0.08967	0.00404	0.04858	0.06113	0.07583	0.1467	0.4111	Significant
ϕ_{bonq}	0.05074	0.03531	0.00125	−0.006018	0.001438	0.01032	0.04664	0.1334	Subsignificant
ϕ_{shbo}	0.03292	0.02493	0.00071	−0.01775	−0.007994	0.001954	0.03312	0.08241	Not significant
ϕ_{bosh}	−0.01133	0.01926	0.00048	−0.0499	−0.04269	−0.03493	−0.01147	0.02766	Not significant
ϕ_{jpbo}	0.08945	0.09993	0.00467	-0.03178	-0.01846	−0.001841	0.06752	0.3702	Not significant
ϕ_{bojp}	0.1762	0.09136	0.00414	0.03627	0.04927	0.06766	0.165	0.3844	Significant
ϕ_{gebo}	0.5833	0.2177	0.01000	0.1867	0.2401	0.3059	0.5752	1.035	Significant
ϕ_{boge}	0.08572	0.07122	0.00305	-0.01649	−0.007184	0.005536	0.07334	0.2571	Not significant
ϕ_{enbo}	0.489	0.2033	0.00946	0.1199	0.1687	0.228	0.4818	0.9241	Significant
ϕ_{boen}	0.1819	0.1261	0.00663	0.02189	0.03725	0.05604	0.1508	0.5201	Significant

4. Conclusion

The empirical results of DC-GC-MSV model are logically correct and convergent. The DIC test result has proved that the DC-GC-MSV model is better and more accurate. (1) Bitcoin has a high degree of independence and is affected neither by the volatility in the major stock markets nor by the volatility in the gold and crude oil market. The volatility of bitcoin futures trading shows more speculation and high risk. Bitcoin can be used as a component of high-risk asset allocation. But Bitcoin still cannot be regarded as a general financial product. (2) Gold is subject to one-way spillover from the stock market, showing that gold is widely recognized as a safe haven product for stock assets. As a financial product, gold has a hedging function in asset allocation. (3) Crude oil has the highest correlation with the stock market. As a highly correlated asset, it is necessary to reduce the proportion of asset decentralized allocation. Investors need to consider a balanced asset allocation among low-correlation assets, medium-correlation assets, and high-correlation assets to reduce risk. Our further research will try to use the MSV model to hedge between different assets.

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 equally to the study.

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