

Research Article

Research on the Dependence Structure and Risk Spillover of Internet Money Funds Based on C-Vine Copula and Time-Varying t -Copula

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Internet money funds (IMFs) are the most widely involved products in the Internet financial products market. This research utilized the C-vine copula model to study the risk dependence structure of IMFs and then introduces the time-varying t -copula model to analyze the risk spillover of diverse IMFs. The results show the following: (1) The risks of Internet-based IMFs, bank-based IMFs, and fund-based IMFs have obvious dependence structure, and the degree of risk dependence among different categories of IMFs is significantly different. (2) There are risk spillover effects among diverse IMFs, and their risk dependence relationship is characterized by cyclical feature. (3) The risk spillover effect among diverse IMFs is pronounced, and dynamic risk dependence between IMFs is characterized by synchronization.

1. Introduction

In recent years, China has paid due attention to the digital transformation of finance and actively promoted the further improvement of the modern digital financial system, which has also stimulated the rapid rise of China's Internet financial products market. Internet financial products as "disintermediated" investment transactions are employing network information technology [1]. Among the Internet financial products, Internet money funds (IMFs) are the most widely participated products. IMFs, also known as Internet money market funds, usually gather idle funds of individual investors and then invest the idle funds by the fund management companies to obtain profit. The traditional money market funds usually implement the "T+2" mode, while the IMFs mostly use "T+0" or "T+1" subscription and redemption mode. Thus, users of IMFs proliferate. Taking Yu'e Bao as an example, its size was up to about 972.415 billion yuan as of the end of the first quarter of 2021.

However, some IMF platforms still have problems such as liquidity risk, maturity mismatch, and APP security loopholes, which further aggravate the uncertainty of IMFs market risk. At the beginning of 2020, the sudden outbreak of the COVID-19 pandemic caused a severe impact on both offline and online finance, making the Internet financial products market more vigorous and vulnerable. Due to the risk dependence relationship, the accumulation and superposition of risks in the Internet financial products market are accelerated, and it also quickly leads to the spread of individual risks to other financial products' markets and forms risk spillovers. In the post-COVID-19 era, it is essential for governments to pay full attention to the prevention and control of risks in the IMFs market.

In this context, does the market risk of IMFs have a dependence structure? Are there risk spillover effects between different categories of IMFs? How does the dependence of IMFs change dynamically? The above questions still need to be further explored and discussed. This research used the Canonical vine copula (C-vine copula) model to examine the risk spillover effect and dynamic dependence among IMFs

based on the time-varying t -copula model to provide valuable references and suggestions for the risk prevention and control of the Internet financial products market.

2. Literature Review

Appropriate monetary liquidity is the primary concern for IMFs. Yang et al. [2] demonstrated that liquidity risk was considered as the main factor in Yu'E Bao's investment strategy. By employing the detailed portfolio holdings of US money market funds, Aftab and Varotto [3] found that these essential players in the shadow banking sector were vulnerable to liquidity shocks. Dong et al. [4] and Chen et al. [5] investigated the linkage effect between Internet finance and commercial banks. Dong et al. [4] found that the development of Internet finance has a negative impact on banks' liquidity. Meanwhile, Chen et al. [5] testified that Internet finance's innovation significantly increased commercial banks' risk-taking behavior.

Some research analyzed the impact of risks presented in the Internet financial products market. Tan et al. [6] conducted an in-depth revelatory case study on Yu'E Bao. Fernandes et al. [7] adopted the autoregressive distributed lag (ARDL) model and analyzed the contribution of digital financial services to financial inclusion in Mozambique. Wang and Ben [8] examined the relationship between online shopping and investment in e-commerce money market funds based on the data from the China Household Finance Survey dataset.

In terms of the relationship between risk and the Internet financial products market, Sung et al. [9] argued that the panic in the IMFs market might be triggered by distrust in the operation of fund managers. Qi et al. [10] found that credit risk and personal information risk were crucial elements that affected the development of Internet finance. From the perspective of the Internet financial products market risk, Xiong et al. [11] proposed a reasonable Internet financial products market portfolio plan for individual or family investment. From the perspective of complex systems, Xu et al. [12] explored the contagion relationship between different risk factors in Internet finance and concluded that risk was transmitted outward through the internal cycle of Internet finance. Fan et al. [13] considered credit risk as an essential issue in the development of Internet finance and conducted an in-depth study on online lending in China.

Copula can effectively measure nonlinear correlation and tail dependence. However, regular copula models cannot build multivariate models. Therefore, Bedford and Cooke [14, 15] proposed the vine copula model to solve this problem. The vine copula model can describe the pairwise correlation structure between variables and enhance the flexibility of modeling. Therefore, the vine copula has been widely used to research risk dependence structure and risk spillover in financial markets. Pourkhanali et al. [16] used C -vine copula and drawable vine copula (D -vine copula) to study the correlation between international financial institutions, and they analyzed the complex dependence among borrowers with an intuitive systematic risk model. Syuhada and Hakim [17] took cryptocurrency as the research object and carried out a risk portfolio on investment according to

the risk dependence structure. Haddad et al. [18] and Xiao [19] both studied the risk dependence structure in the stock market using the vine copula, and Xiao [19] further looked at the risk spillovers of stock markets during periods of volatility and depression.

Considering the time-varying characteristics of variables, some researchers used time-varying copula models to study the dynamic dependence structure and spillover effects among financial markets. Yan et al. [20] studied the tail dependence of financial markets with the time-varying t -copula model and gave the optimal portfolio choice. Some researchers have also used the time-varying copula model to study a particular financial market. Duong and Huynh [21] and Wu et al. [22] studied the risk in the stock market. The latter focused on the impact of RMB exchange rate and equity spillover effects and found a positive relationship between them. Han et al. [23] used a time-varying copula to analyze the dynamic dependence between financial assets and constructed a value-at-risk (VaR) portfolio model. Rehman et al. [24, 25] studied the extreme dependence and risk spillover relationship between Bitcoin and precious metals using time-varying copula and later studied the dependence structure and found the existence of risk spillover effect between Bitcoin and Islamic stocks.

Existing research studies have mainly focused on analyzing single risk or portfolio risk in the financial market, and few quantitative analyses and empirical studies have been conducted on the risk dependence of different categories of IMFs and the dynamic risk spillover between them. In this context, it is of practical significance to study the risk dependence of IMFs and analyze the direction and intensity of risk spillover of IMFs for the stable, sustainable development of the Internet financial products market.

3. Data Sources and Preprocessing

3.1. Data Selection. The sample data were collected from the Wind database, which divided IMFs into three categories, including Internet-based IMFs (INTE), bank-based IMFs (BANK), and fund-based IMFs (FUND). INTE mainly refers to IMFs docked by the third-party payment institutions; BANK refers to IMFs docked by banks, while FUND refers to IMFs docked by the fund companies. Our research followed the categories in Wind. Five representative funds of each category were selected, respectively. The 15 sample IMFs were chosen according to their category, fund size, year of establishment, industry representativeness, and so on. The basic information of sample IMFs is shown in Table 1.

To ensure the continuity of the data, the seven-day annualized returns (%) of the 15 IMFs are recorded as $A_i (i = 1, \dots, 15)$. The data covers January 31, 2016, to January 31, 2020. There are 1,462 observations of each fund return series after removing the invalid values, totaling 21,930 observations.

3.2. Descriptive Statistics. The first-order difference of the original data was used to obtain the logarithmic seven-day annualized return series of the sample IMFs, denoted as

TABLE 1: Sample information.

| Category | Fund companies | IMFs | Fund size (billion) | Date of establishment | Experimental variables |
|----------|---|---------------------------|---------------------|-----------------------|------------------------|
| INTE | Alipay | Tianhong Yu'E Bao | 1093.60 | 2013-05-29 | A1 |
| | Baidu | Huaxia Xianjin Zengli A/E | 29.13 | 2004-04-07 | A2 |
| | Tencent | Huitianfu Quan'E Bao | 90.95 | 2013-12-13 | A3 |
| | Wangyilicai | Huitianfu Xianjin Bao | 42.86 | 2013-09-12 | A4 |
| | JD | JiashiHuoqianbao A | 26.86 | 2014-03-17 | A5 |
| BANK | China Construction Bank | Jianxin Xianjintianli A | 156.35 | 2014-09-17 | A6 |
| | Industrial and Commercial Bank of China | Gongyin Xinjin A | 6.81 | 2014-01-27 | A7 |
| | Bank of Communications | Nanfang Xianjintong E | 9.48 | 2004-03-05 | A8 |
| | China Minsheng Banking | Minsheng Jiayinxianjin A | 19.77 | 2013-10-18 | A9 |
| | Industrial Bank | Xingquan Tianli Bao | 87.49 | 2014-02-27 | A10 |
| FUND | GF Fund Management | Guangfa Yindaizi A | 16.37 | 2014-01-10 | A11 |
| | Bosera Funds | Boshi Xianjin A | 163.72 | 2004-01-06 | A12 |
| | Galaxy Fund Management | Yinhe Yinfu A | 18.28 | 2004-12-20 | A13 |
| | Rongtong Fund | Rongyitong Zhifu A | 31.12 | 2006-01-19 | A14 |
| | Fullgoal Fund | Fuguo Fuqianbao | 50.17 | 2014-05-07 | A15 |

Note: fund size as of January 31, 2020.

$B_i (i = 1, \dots, 15)$ to reflect the fluctuation of fund returns. We calculated B_i as follows:

$$B_i = \ln A_i - \ln A_{i-1}. \quad (1)$$

Table 2 presents the results of the descriptive analysis.

The average yield series of INTE, BANK, and FUND was used as the return series and subjected to first-order differencing. The descriptive statistics after first-order differencing are shown in Table 3.

According to Tables 2 and 3, the mean value of the log-return series $B_i (i = 1, \dots, 15)$ and three categories of IMFs are close to 0 and have the characteristics such as "fat-tail" and "nonnormality," so the t-distribution can be considered to fit the log-return series of the three categories.

3.3. Stability Test. Heteroskedasticity and autocorrelation are common features of the time series of IMFs. Therefore, the stability test was performed for $B_i (i = 1, \dots, 15)$. According to Table 4, it can be found that the ADF test statistics are statistically significant, indicating that $B_i (i = 1, \dots, 15)$ and the log-return series of three categories of IMFs are stable.

3.4. ARCH Effect Test. Before the ARCH effect test, INTE, BANK, and FUND should be tested for autocorrelation. Taking the BANK as an example, firstly, the BANK series were tested for autocorrelation at lagged 36th order until the absolute value of Q-Stat at 36th order was greater than 0. The P value of Q-Stat results showed that it passed the significance test, indicating the existence of autocorrelation in the BANK series. According to the results of the BANK series autocorrelation test, AR (1) and AR (2) were established for comparison, and the orders were determined by AIC and SC minimum criteria. The results showed that AR (2) had the

better results and the regression coefficients of AR (1) and AR (2) were significant. Finally, the ARCH-LM test was performed, and the length of the lag was set to 2. The results showed that the P value of the F-statistic was 0.002. Therefore, the BANK series had an ARCH effect, and the GARCH model could be applied later.

Similarly, the above tests were performed with the INTE and FUND series. The results showed autocorrelation and ARCH effects in INTE, BANK, and FUND, which provided the preconditions for constructing a model using the marginal distribution to describe the risk dependence among IMFs.

4. Model Design

The vine copula model was introduced to portray the risk dependence structure among multiple IMFs, forming a multilayer tree structure diagram and then realizing the measurement of multiple dependence structures. Subsequently, a time-varying t -copula model was introduced to calculate the risk spillover ΔCoVaR and analyze the changes of dynamic dependence among diverse IMFs.

4.1. Edge Distribution Model. The data tests reveal that the selected INTE, BANK, and FUND series are biased, non-normal, peak fat-tail, autocorrelated, and volatility aggregated. Therefore, when modeling and analyzing the log-return, it is essential to eliminate the autocorrelation, volatility aggregation, and so on. Therefore, the AR model and GARCH model can be used. Katsiampa [26] and Ma et al. [27] pointed out that the GARCH model was more accurate for finance-related time series, and the t-distribution could better portray the nonnormal characteristics of finance-related time series data. Owing to that fact, the marginal

TABLE 2: Descriptive analysis of log-return series of sample IMFs.

| Category | Series | Mean value | Std. deviation | Skewness | Kurtosis | Jarque–Bera | <i>P</i> value |
|----------|--------|------------|----------------|----------|----------|-------------|----------------|
| INTE | B1 | 0.0002 | 0.109 | −0.489 | 7.191 | 1127.204 | ≤0.001 |
| | B2 | 0.0002 | 0.135 | 0.284 | 32.035 | 51339.78 | ≤0.001 |
| | B3 | 0.0004 | 0.088 | −0.469 | 25.434 | 30690.48 | ≤0.001 |
| | B4 | 0.0003 | 0.055 | 0.256 | 72.188 | 291426.2 | ≤0.001 |
| | B5 | 0.0013 | 0.111 | 0.580 | 48.356 | 125313.6 | ≤0.001 |
| BANK | B6 | 0.0002 | 0.027 | 0.127 | 15.970 | 10244.57 | ≤0.001 |
| | B7 | 0.0019 | 0.136 | −0.499 | 42.192 | 93567.38 | ≤0.001 |
| | B8 | 0.0004 | 0.070 | 0.099 | 38.983 | 78823.13 | ≤0.001 |
| | B9 | 0.0007 | 0.069 | 0.274 | 17.301 | 12467.58 | ≤0.001 |
| | B10 | 0.0002 | 0.061 | 0.052 | 12.858 | 5916.55 | ≤0.001 |
| FUND | B11 | 0.0004 | 0.073 | −0.354 | 56.419 | 173740.7 | ≤0.001 |
| | B12 | 0.0007 | 0.072 | −0.055 | 31.502 | 49454.89 | ≤0.001 |
| | B13 | 0.0013 | 0.344 | 0.336 | 26.874 | 34723.43 | ≤0.001 |
| | B14 | 0.0005 | 0.114 | 0.503 | 40.802 | 87051.22 | ≤0.001 |
| | B15 | 0.0003 | 0.154 | 0.579 | 57.251 | 179249.7 | ≤0.001 |

TABLE 3: The descriptive statistics after first-order differencing.

| Category | Mean value | Std. deviation | Skewness | Kurtosis | Jarque–Bera | <i>P</i> value |
|----------|------------|----------------|----------|----------|-------------|----------------|
| INTE | 0.0005 | 0.041 | 0.034 | 13.020 | 6112.605 | ≤0.001 |
| BANK | 0.0007 | 0.038 | 0.082 | 16.510 | 11113.43 | ≤0.001 |
| FUND | 0.0006 | 0.083 | 0.393 | 18.909 | 15445.83 | ≤0.001 |

TABLE 4: Results of the log-return series test for INTE, BANK, and FUND.

| Category | Experimental variables | ADF test | <i>P</i> value | ADF test | <i>P</i> value |
|----------|------------------------|-----------|----------------|-----------|----------------|
| INTE | B1 | −5.397684 | ≤0.001 | −8.670909 | ≤0.001 |
| | B2 | −10.85343 | ≤0.001 | | |
| | B3 | −16.57159 | ≤0.001 | | |
| | B4 | −15.58782 | ≤0.001 | | |
| | B5 | −12.29044 | ≤0.001 | | |
| BANK | B6 | −10.0594 | ≤0.001 | −17.08869 | ≤0.001 |
| | B7 | −14.9402 | ≤0.001 | | |
| | B8 | −15.2912 | ≤0.001 | | |
| | B9 | −14.6561 | ≤0.001 | | |
| | B10 | −10.0251 | ≤0.001 | | |
| FUND | B11 | −11.47712 | ≤0.001 | 16.81036 | ≤0.001 |
| | B12 | −10.83287 | ≤0.001 | | |
| | B13 | −13.06646 | ≤0.001 | | |
| | B14 | −22.30595 | ≤0.001 | | |
| | B15 | −11.83497 | ≤0.001 | | |

distributions of INTE, BANK, and FUND were estimated using the AR (1)-GARCH (1, 1)-*t* model. The results are shown in Table 5.

According to the results in Table 5, the AIC and SC values of the log-return series model of the IMFs are relatively small, and the model can be considered as a better fit for the data. To estimate the residual series of B_i ($i = 1, \dots, 15$), the standardized residual series were derived, and the new series was obtained by MATLAB. According to the *K*-*S* test results, it can be considered that the marginal distribution sequence of IMFs B_i ($i = 1, \dots, 15$) is independent and identically distributed in the standard uniform distribution. Then, the new residual series was analyzed by the copula model.

TABLE 5: The estimation results of AR (1)-GARCH (1, 1)-*t* model.

| Category | Parameter | | | |
|----------|-----------|---------|----------|---------------------------|
| | AIC | SC | <i>N</i> | <i>K</i> - <i>S</i> value |
| INTE | −3.6822 | −3.6713 | 2.0002 | 0.0268 |
| BANK | −4.0265 | −4.0156 | 2.9701 | 0.0176 |
| FUND | −2.8131 | −2.8022 | 2.0350 | 0.0204 |

4.2. C-Vine Structure and Modeling. The vine structure overcomes the limitation that traditional copula cannot accurately measure the different dependence structures among multiple variables. It divides the multivariable into binary structures and selects the appropriate copula function to establish the joint distribution according to the specific

characteristics between variables. There are two common vine structures: C -vine copula and D -vine copula. The C -vine copula is suitable for the situation of primary variables leading to other variables, and the D -vine copula is ideal for the case that the relationship between variables is relatively independent [14, 28]. The parameters were estimated by the C -vine copula and D -vine copula, respectively (for results, see Table 6).

According to Table 6, the AIC and BIC values in C -vine are smaller than those in D -vine. Considering the likelihood and the model selection criterion of minimizing AIC and

TABLE 6: Parameters of C -vine copula and D -vine copula.

| Copula | AIC | BIC | Log-likelihood |
|-----------|----------|----------|----------------|
| C -vine | -71.0679 | -55.2073 | 38.534 |
| D -vine | -69.8468 | -53.9862 | 37.923 |

BIC, this research selected the C -vine copula to analyze the risk dependence structure of the three categories of IMFs.

The decomposition of the C -vine copula is specified as

$$f(x_1, x_2, \dots, x_n) = \prod_{k=1}^n f(x_k) \times \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{j, j+i|1, \dots, j-1}(F(x_j|x_1, \dots, x_{j-1}), F(x_{j+i}|x_1, \dots, x_{j-1})), \quad (2)$$

where F is the conditional distribution, f is the density function, and c is the conditional density.

4.3. Time-Varying t -Copula Model and ΔCoVaR . Considering the different dependence and time-varying characteristics of INTE, BANK, and FUND, we established a time-varying t -copula model to describe the dynamic dependence relationship between INTE, BANK, and FUND more accurately and evaluate their linkage correlation and contagion correlation. Considering the dynamic and complex nature of the risk linkage process, the idea of Tse and Tsui [29] was introduced here to portray the dynamic change of the dependence coefficient of the time-varying t -copula model:

$$\rho_t = (1 - m - n) \cdot R + m \cdot r_{t-1} + n \cdot \rho_{t-1}, \quad (3)$$

where ρ is the linear correlation coefficient of the two probabilistically integrated transformed random variables, r_{t-1} is the correlation coefficient of the samples within the rolling window period, R is the covariance of the sample series, and m and n are the unknown parameters to be estimated in the equation.

The GARCH model was used to calculate the VaR to predict the volatility of INTE, BANK, and FUND and to model their volatility patterns. The GARCH (1, 1) model is specified as

$$y_t = \mu_t + a_t, \quad (4)$$

$$a_t = \sigma_t \xi_t, \xi_t \sim \text{i.i.d.}(0, 1), \quad (5)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \quad (6)$$

where y_t is the time series of the rate of return, a_t is the disturbance of rate of return, σ_t^2 is the conditional variance, ξ_t is the independent identically distributed white noise sequence, and $\alpha_0, \alpha_1, \beta_1$ are model parameters, $\alpha_0 > 0, \alpha_1 > 0, \beta_1 > 0$.

CoVaR refers to the risk that other IMFs are affected during a certain confidence level when certain IMFs generate risk in a certain time period. The equation of CoVaR is as follows:

$$P(I^{a,b} \leq \text{CoVaR}_q^{a,b}) = q, \quad (7)$$

where q is the confidence level and $I^{a,b}$ is the VaR of fund a and fund b .

Adrian and Brunnermeier [30] captured the tail dependence between the financial system as a whole and specific institutions by using ΔCoVaR . Based on the research of Adrian and Brunnermeier, the risk-added value ΔCoVaR was used as an index to measure risk spillover. The calculation for ΔCoVaR can be summarized as

$$\Delta\text{CoVaR}_q^{a,b} = \text{CoVaR}_q^{a,b} - \text{VaR}_q^a, \quad (8)$$

where $\Delta\text{CoVaR}_q^{a,b}$ is the risk spillover from IMF a to IMF b and VaR_q^a is the unconditional VaR of IMF a .

5. Empirical Results and Analysis

5.1. Analysis of Risk Dependence Structure. The C -vine copula was used to model the dependence structure among IMFs. Kendall's rank correlation coefficient τ between two variables was calculated by the R language (see Table 7).

Each layer of the C -vine has a key node, which has a dominant influence on other nodes. According to the results in Table 7, FUND was selected as the pivotal variable in the C -vine copula structure. Figure 1 shows the dependence structure based on the C -vine copula.

As can be seen in Figure 1, there are two trees: T_j ($j = 1, 2$). The main pivot point in the first layer is FUND 1, which is connected to the BANK 2 and the INTE 3, with each edge corresponding to the pair-copula density.

In order to choose a suitable copula model to measure the dependence structure of the IMFs, it is necessary to observe the distribution sequence scatter plot and frequency diagram. Taking the first layer structure as an example, the plots and diagrams are shown in Figures 2–5.

According to Figures 2 and 4, although the scatter distribution area is wide, the distribution is more obvious on the main diagonal. Figures 3 and 5 can visually show the tail correlation between the two sequences, showing an upper and lower tail correlation between BANK and FUND.

TABLE 7: Kendall rank correlation coefficients among the IMFs.

| | INTE | BANK | FUND | Summation |
|------|--------|--------|--------|-----------|
| INTE | 1 | 0.0586 | 0.0628 | 0.1214 |
| BANK | 0.0586 | 1 | 0.0781 | 0.1367 |
| FUND | 0.0628 | 0.0781 | 1 | 0.1409 |

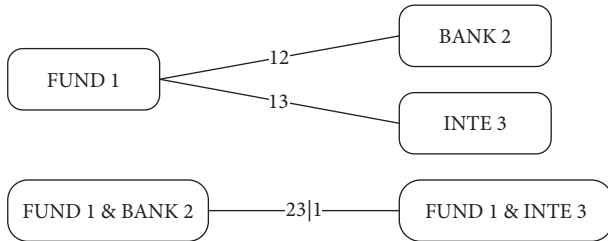


FIGURE 1: Dependence structure diagram based on C-vine copula.

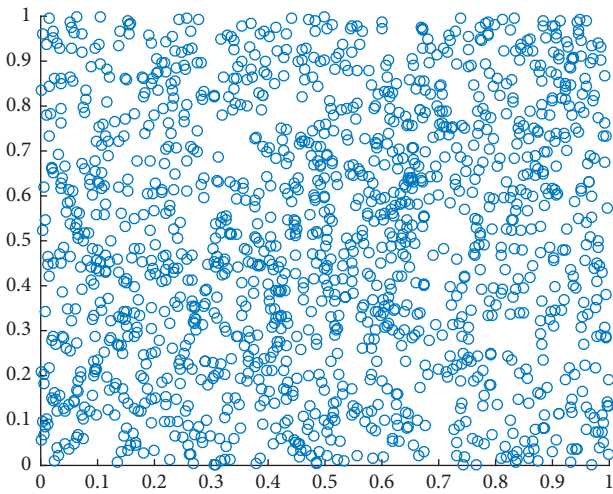


FIGURE 2: INTE-FUND scatter plot.

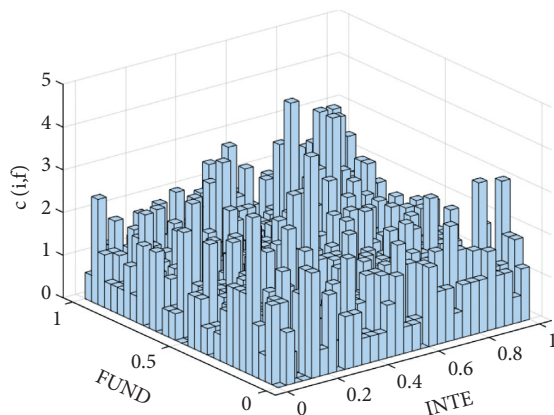


FIGURE 3: INTE-FUND frequency diagram.

The t -copula, Gaussian copula, and Clayton copula were modeled, respectively. The parameter estimation results (see Table 8) show that t -copula was the most appropriate model in this study by the AIC criterion.

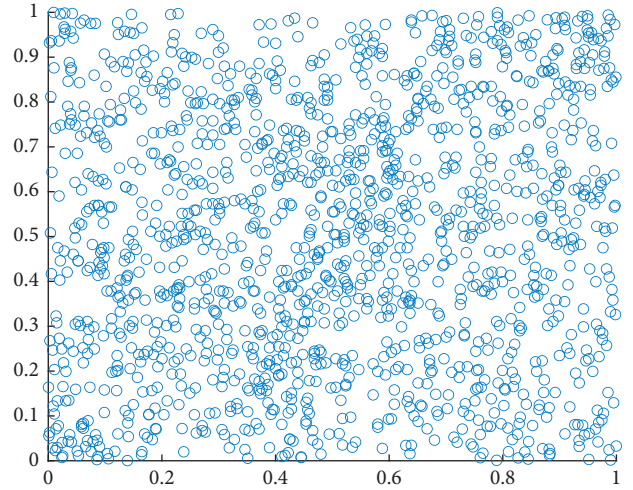


FIGURE 4: BANK-FUND scatter plot.

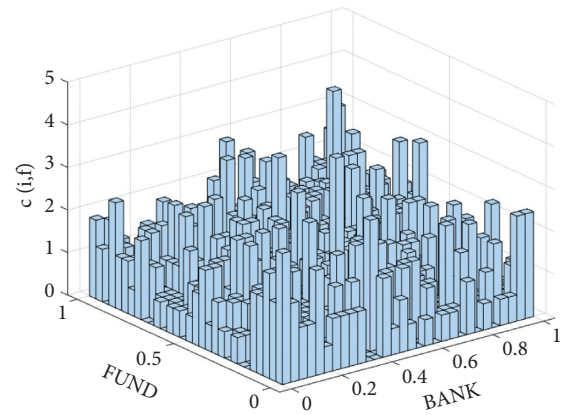


FIGURE 5: BANK-FUND frequency diagram.

FUND is the critical node in the relationship among IMFs. As seen from the first layer in Table 8, each category of IMFs shows high unconditional dependence. In the second layer, the INTE-BANK|FUND indicates a conditional correlation, which means that the FUND must be used as known information for the C-vine copula when INTE is fitted with the BANK.

Among them, the correlation coefficients of INTE-FUND and BANK-FUND in the first layer are positive, and the correlation coefficient of BANK-FUND is the highest, which indicates that the return rate of BANK-FUND is more likely to move in the same direction. In the second layer, the correlation coefficient of INTE-BANK is positive when FUND is taken as a known condition, and the return of BANK and INTE will also move in the same direction.

5.2. Measure of Risk Spillover Effects. Based on the above results, the time-varying t -copula model was introduced as a way to calculate the CoVaR values and the VaR values between IMFs. Then, the Δ CoVaR values of spillover effects were calculated to analyze the direction and intensity of risk spillover among INTE, BANK, and FUND.

TABLE 8: Parameter estimation results of IMFs.

| Number of layers | Related funds | Rho correlation coefficient | Degree of freedom | AIC |
|------------------|----------------|-----------------------------|-------------------|----------|
| First layer | INTE-FUND | 0.0757 | 13.640 | -8.6175 |
| | BANK-FUND | 0.1093 | 5.776 | -48.6754 |
| Second layer | INTE-BANK FUND | 0.0834 | 13.768 | -13.5544 |

Note: the results are calculated by MATLAB.

The VaR values of the INTE, BANK, and FUND series and their mean values are shown in Table 9.

The mean VaR value of the FUND is 0.2034, which is much larger than the INTE (0.1169) and the BANK (0.0830), indicating that the FUND products are exposed to the most significant risk. The possible reason is that the FUND's asset allocation is much more prominent in bonds and securities, and its cash holdings are smaller than the INTE and BANK. From a temporal perspective, the VaR values of the BANK and FUND both show an overall upward trend from 2016 to 2019. Meanwhile, the INTE shows a fluctuating decline, indicating that the risk regulation measures for INTE have played a specific role in recent years.

The parameters were estimated by the time-varying t -copula model. Results are shown in Table 10.

Monte Carlo simulation was carried out based on the results in Table 10. The results of ΔCoVaR are shown in Table 11.

The sequence diagrams of the pair-to-pair risk spillover relationship among IMFs based on the ΔCoVaR results are shown in Figures 6–8.

Figures 6–8 reveal that the IMFs' risk spillover effects show periodic characteristics. IMFs have more obvious risk spillovers around September 2017, around April 2019, and after October 2019, respectively. The occurrence probability of risk spillover among IMFs is strongly related to the central bank's policy; for most investments of IMFs are cash, bank deposits, central bank bills, and so on. On September 30, 2017, the People's Bank of China cut the reserve requirement ratio by 0.5%, and in March 2019, ten-year government bond yields in China touched the lowest point of the year. Those policies might explain the risk spillover effects in IMFs. Thus, changes in macroeconomic policy play an influential role in the risk spillover of the IMFs market.

The risk spillover among diverse IMFs is directional. From the perspective of the year-by-year risk spillover effect, the ΔCoVaR from BANK to FUND is enormous and increasing year by year from 2016 to 2018. While the ΔCoVaR from FUND to BANK is relatively small, indicating that when the BANK produces risks, they are more likely to infect the FUND products. Nevertheless, when FUND's risk spillover occurs, it will not have a significant impact on BANK.

The empirical study of Dong et al. [4] and Chen et al. [31] demonstrated that there was mutual causality between Internet finance and the banking industry. On the whole, our empirical results on the risk spillover effect between INTE and BANK are similar to their research, but still, there are differences.

TABLE 9: VaR value for INTE, BANK, and FUND (2016–2019).

| | INTE | BANK | FUND |
|------------|--------|--------|--------|
| 2016 | 0.1169 | 0.0645 | 0.1073 |
| 2017 | 0.1239 | 0.0706 | 0.1410 |
| 2018 | 0.1141 | 0.0726 | 0.1626 |
| 2019 | 0.1225 | 0.1222 | 0.3805 |
| Mean value | 0.1169 | 0.0830 | 0.2034 |

In terms of spillover intensity, the absolute value of ΔCoVaR from INTE to BANK is greater than that from BANK to INTE, which indicates that the volatility spillover effect from INTE to BANK is more substantial. The ΔCoVaR from INTE to FUND is relatively small, while the risk spillover from FUND to INTE is relatively large. That result demonstrates that INTE would be affected by FUND when FUND is at risk. But on the contrary, FUND is not obviously affected by INTE. In 2019, although the two-way risk spillover value between BANK and INTE was similar, the spillover direction between BANK and FUND changed. When the risk of FUND occurs, it is likely to be transmitted to BANK.

In general, there is indeed a risk spillover phenomenon between diverse IMFs in recent years. (1) FUND has a significant influence on both BANK and INTE. There is a clear trend risk spillover from the FUND to other IMFs, indicating that once a certain risk was generated by the FUND products, it would easily affect the whole IMFs market. Figure 8 also shows that the spillover peaked around October 2019, indicating that both INTE and BANK are vulnerable to FUND. FUND products share part of the risk generated by INTE and BANK products and simultaneously increase the probability of risk occurrence for INTE and BANK products. (2) The mean value of risk spillover from BANK to FUND is the largest, while the risk spillover effect of INTE to BANK shows a fluctuating downward trend.

5.3. Dynamic Dependence Analysis of Risk Spillover. In order to show the changes of dependence among INTE, BANK, and FUND, time-varying t -copula was used for the dynamic dependence coefficient sequences (see Figures 9–11).

Figures 9–11 show that the dynamic correlation coefficients between INTE, BANK, and FUND fluctuate up and down in the range of $[-0.3, 0.3]$, which is quite different from the Kendall rank correlation coefficient results obtained by the C -vine copula model. It indicates that the Kendall rank correlation coefficients are not accurate to show the risk dependence between IMFs. The dynamic correlation coefficient between the BANK and the FUND remains at 0.09 and basically does not fluctuate, which is related to the value

TABLE 10: Results of time-varying t -copula parameter estimation for IMFs.

| | Parameter 1 | Parameter 2 | Parameter 3 | AIC | LogL |
|-----------|-------------|-------------|-------------|----------|--------|
| INTE-BANK | 18.5768 | 0.0344 | 0.8705 | -15.9343 | 10.967 |
| INTE-FUND | 13.6868 | 0.0439 | 0.7623 | -11.5089 | 8.754 |
| BANK-FUND | 5.3921 | 0.0000 | 0.9301 | -43.9061 | 24.953 |

TABLE 11: Δ CoVaR value for INTE, BANK, and FUND (2016–2019).

| | INTE \rightarrow BANK | BANK \rightarrow INTE | BANK \rightarrow FUND | FUND \rightarrow BANK | FUND \rightarrow INTE | INTE \rightarrow FUND |
|------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| 2016 | -0.0348 | 0.0176 | 0.0639 | 0.0109 | 0.0117 | 0.0020 |
| 2017 | -0.0367 | 0.0166 | 0.0789 | -0.0154 | -0.0173 | -0.0003 |
| 2018 | -0.0254 | 0.0161 | 0.0790 | -0.0368 | -0.0371 | 0.0114 |
| 2019 | -0.0301 | -0.0298 | 0.1307 | -0.2434 | -0.2515 | 0.0066 |
| Mean value | -0.0289 | 0.0050 | 0.0882 | -0.0767 | -0.0786 | 0.0078 |

Note: \rightarrow denotes the direction of risk spillover.

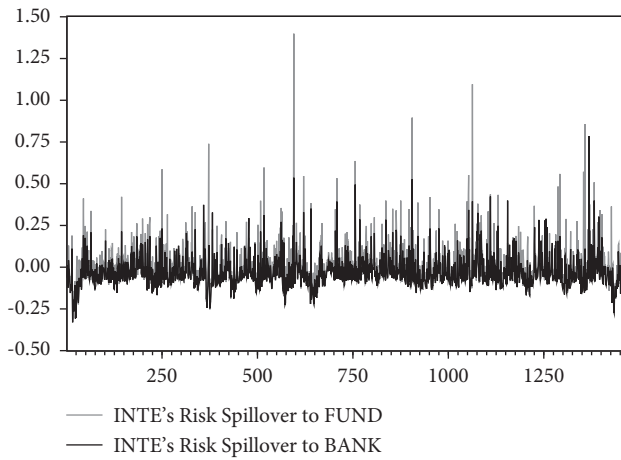


FIGURE 6: INTE's risk spillover to BANK and FUND.

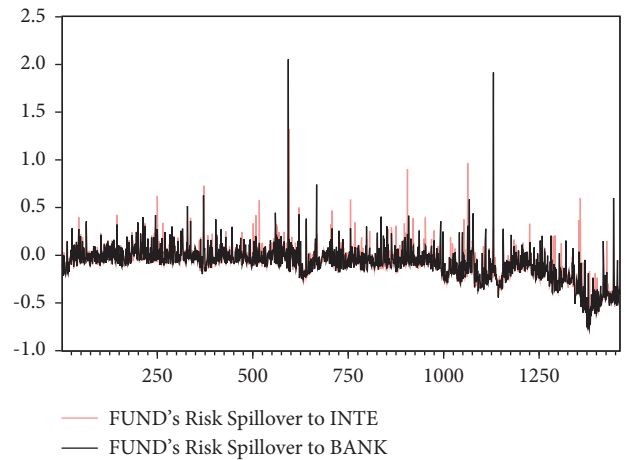


FIGURE 8: FUND's risk spillover to INTE and BANK.

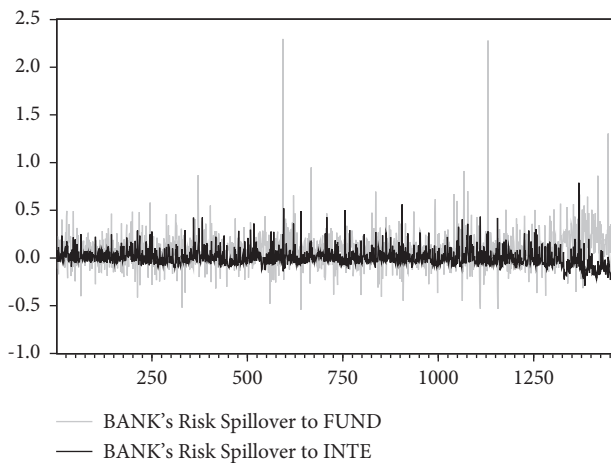


FIGURE 7: BANK's risk spillover to INTE and FUND.

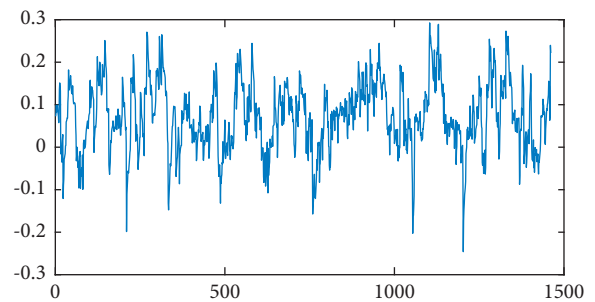


FIGURE 9: INTE and BANK sequence diagram.

of parameter 3 in Table 10, and the trend of the dynamic correlation coefficient changes more smoothly when the value of parameter 3 is closer to 1.

The estimated values of parameter 3 in the time-varying t -copula model are 0.8705, 0.7623, and 0.9301, indicating

that the trend of the dependence change between the BANK and the FUND is stable. The obtained dynamic correlation coefficients were subjected to descriptive statistics. The results are shown in Table 12.

The mean value of INTE-BANK is 0.0721, with a positive correlation ratio of 73.5%, while INTE-FUND is 0.0513 and 70.7%, and BANK-FUND is 0.0940 and 100%. These results indicate that there is a positive correlation between INTE and BANK, INTE and FUND, and BANK and FUND during most of the trading time. Relatively, BANK-FUND always

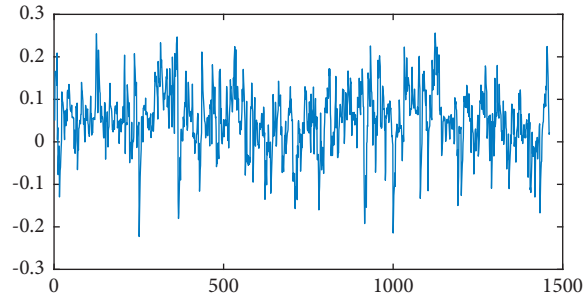


FIGURE 10: INTE and FUND sequence diagram.

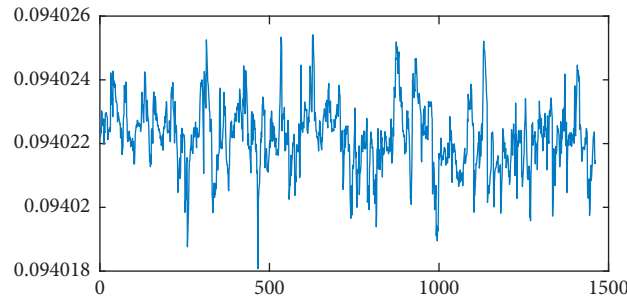


FIGURE 11: BANK and FUND sequence diagram.

TABLE 12: Statistical characteristics of dynamic correlation coefficients of IMFs.

| Correlation coefficient | Mean value | Standard deviation | Maximum value | Minimum value | Percentage of positive correlation | Percentage of negative correlation |
|-------------------------|------------|--------------------|---------------|---------------|------------------------------------|------------------------------------|
| INTE-BANK | 0.0721 | 0.08 | 0.29 | -0.25 | 73.5 | 26.5 |
| INTE-FUND | 0.0513 | 0.05 | 0.26 | -0.22 | 70.7 | 29.3 |
| BANK-FUND | 0.0940 | 0.00 | 0.09 | 0.09 | 100 | 0.00 |

maintains a strong positive correlation during the trading process. Considering that the rise and fall of the price of BANK products are likely to coincide with FUND products, some banks also have business relations with fund companies, leading to a cross-influence between BANK and FUND.

In terms of the valley and the peak value, INTE-BANK and INTE-FUND do not differ much, and they both show similar periodic changes. The maximum and minimum values of BANK-FUND differ in a tiny order of magnitude. Due to the massive scale of INTE and the wide range of products covered, it will have a greater correlation with BANK and FUND in certain time periods, and the probability of having the same or opposite change in returns is high. In terms of volatility (standard deviation), BANK-FUND fluctuates very smoothly, while the difference of standard deviation between INTE-BANK and INTE-FUND is 0.03, indicating that the fluctuation degree of INTE-BANK is the largest, followed by INTE-FUND. The sequence diagrams (Figures 9–11) also show that INTE-BANK and INTE-FUND have been in a state of greater volatility, indicating that the FUND and BANK yields maintain a weak positive correlation, and the positive or negative relationship between the INTE and other IMFs yields change over time.

In summary, from January 31, 2016, to January 31, 2020, the INTE-BANK and the INTE-FUND show a significant positive correlation in most of the trading time. As a whole, the dependence relationship fluctuates a lot, and those IMFs' profits and losses are synchronous. Among them, the BANK-FUND maintains a positive correlation during the trading process, and its degree of fluctuation is almost zero, which means that the trend of dependence and association between them is the most stable.

6. Conclusions

Our research selected 15 IMFs for empirical analysis. The C-vine copula model was chosen to analyze the dependence structure of INTE, BANK, and FUND. Then the time-varying t -copula model was introduced to calculate the risk spillover between them. The conclusions obtained are as follows.

Firstly, there is a well-defined risk dependence structure among INTE, BANK, and FUND. Secondly, risk spillovers do exist among the IMFs, their risk spillovers are similar in periodicity, and the risk spillover among different categories has directionality. Thirdly, both INTE-BANK and INTE-FUND show positive correlation in most trading time and

both fluctuate a lot, while BANK-FUND has maintained a significant positive correlation during the trading process and has a more stable dependence relationship.

This research sheds some light on the research on the dependence structure and risk spillover of IMFs, and the findings imply that investors should clearly understand that no IMFs can guarantee an absolute return. They should pay attention to the return scale and various risk indicators of IMFs. And investors can further optimize their investment portfolios based on the risk dependence relationship between different IMFs.

Still, there are some limitations to this research. For instance, as we used 15 IMFs for the sample, further expansion of the sample size would be considered to obtain more accurate research results. In addition, we used the *C*-vine copula and *D*-vine copula in the empirical test, and we would take more copula functions into account in future research and select the best fitting copula model.

Data Availability

All data used to support the findings of this study are downloaded from the Wind database, and the data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

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References

- [1] J. Zhang, S. Zhu, W. Yan, and Z. Li, "The construction and simulation of internet financial product diffusion model based on complex network and consumer decision-making mechanism," *Information Systems and e-Business Management*, vol. 18, no. 4, pp. 545–555, 2020.
- [2] X. Yang, S. Mao, H. Gao, Y. Duan, and Q. Zou, "Novel financial capital flow forecast framework using time series theory and deep learning: a case study analysis of Yu'E Bao transaction data," *Ieee Access*, vol. 7, pp. 70662–70672, 2019.
- [3] Z. Aftab and S. Varotto, "Liquidity and shadow banking," *Journal of International Money and Finance*, vol. 99, Article ID 102080, 2019.
- [4] J. Dong, L. Yin, X. Liu et al., "Impact of internet finance on the performance of commercial banks in China," *International Review of Financial Analysis*, vol. 72, Article ID 101579, 2020.
- [5] Z. Chen, K. Li, and L.-Y. He, "Has internet finance decreased the profitability of commercial banks?: evidence from China," *Emerging Markets Finance and Trade*, vol. 56, no. 13, pp. 3015–3032, 2020.
- [6] T. Tan, Y. Zhang, Y. Zhang, C. Suang, and C. Ge, "Empowerment of grassroots consumers: a revelatory case of a Chinese fintech innovation," *Journal of the Association for Information Systems*, vol. 22, no. 1, pp. 179–203, 2021.
- [7] C. Fernandes, M. R. Borges, and J. Caiado, "The contribution of digital financial services to financial inclusion in Mozambique: an ARDL model approach," *Applied Economics*, vol. 53, no. 3, pp. 400–409, 2021.
- [8] Z. Wang and S. Ben, "Effect of consumers' online shopping on their investment in money market funds on ecommerce platforms," *Information Systems and e-Business Management*, 2021, In press.
- [9] S. Sung, D. Chun, H. Cho et al., "Hedge fund market runs during financial crises," *Economic Research-Ekonomika Istraiwanja*, vol. 4, pp. 1–26, 2020.
- [10] S. Q. Qi, K. J. Jin, B. S. Li et al., "The exploration of Internet finance by using neural network," *Journal of Computational and Applied Mathematics*, vol. 369, Article ID 112630, 2020.
- [11] J. Xiong, C. Zhang, G. Kou et al., "Optimizing long-term bank financial products portfolio problems with a multiobjective evolutionary approach," *Complexity*, vol. 2020, Article ID 3106097, 18 pages, 2020.
- [12] R. J. Xu, C. M. Mi, R. Mierziak et al., "Complex network construction of Internet finance risk," *Physica A-Statistical Mechanics and Its Applications*, vol. 540, Article ID 122930, 2020.
- [13] S. S. Fan, Y. B. Shen, and S. N. Peng, "Improved ML-based technique for credit card scoring in Internet financial risk control," *Complexity*, vol. 2020, Article ID 8706285, 14 pages, 2020.
- [14] T. Bedford and R. M. Cooke, "Probability density decomposition for conditionally dependent random variables modeled by vines," *Annals of Mathematics and Artificial Intelligence*, vol. 32, no. 1-4, pp. 245–268, 2001.
- [15] T. Bedford and R. M. Cooke, "Vines: a new graphical model for dependent random variables," *Annals of Statistics*, vol. 30, no. 4, pp. 1031–1068, 2002.
- [16] A. Pourkhanali, J.-M. Kim, L. Tafakori, and F. A. Fard, "Measuring systemic risk using vine-copula," *Economic Modelling*, vol. 53, pp. 63–74, 2016.
- [17] K. Syuhada and A. Hakim, "Modeling risk dependence and portfolio VaR forecast through vine copula for cryptocurrencies," *PLoS One*, vol. 15, no. 12, Article ID e0242102, 2020.
- [18] H. B. Haddad, I. Mezghani, and M. A. Dohaiman, "Common shocks, common transmission mechanisms and time-varying connectedness among Dow Jones Islamic stock market indices and global risk factors," *Economic Systems*, vol. 44, no. 2, Article ID 100760, 2020.
- [19] Y. Xiao, "The risk spillovers from the Chinese stock market to major East Asian stock markets: a MSGARCH-EVT-copula approach," *International Review of Economics & Finance*, vol. 65, pp. 173–186, 2020.
- [20] Z. Yan, Z. Chen, G. Consigli, J. Liu, and M. Jin, "A copula-based scenario tree generation algorithm for multiperiod portfolio selection problems," *Annals of Operations Research*, vol. 292, no. 2, pp. 849–881, 2020.
- [21] D. Duong and T. L. D. Huynh, "Tail dependence in emerging ASEAN-6 equity markets: empirical evidence from quantitative approaches," *Financial Innovation*, vol. 6, no. 1, pp. 1–26, 2020.
- [22] X. Wu, S. Zhu, and S. Wang, "Research on information spillover effect of the RMB exchange rate and stock market

- based on R-vine copula,” *Complexity*, vol. 2020, Article ID 2492181, 12 pages, 2020.
- [23] Y. Han, P. Li, J. Li, and S. Wu, “Robust portfolio selection based on copula change analysis,” *Emerging Markets Finance and Trade*, vol. 56, no. 15, pp. 3635–3645, 2020.
- [24] M. U. Rehman, “Do bitcoin and precious metals do any good together? An extreme dependence and risk spillover analysis,” *Resources Policy*, vol. 68, Article ID 101737, 2020.
- [25] M. U. Rehman, N. Asghar, and S. H. Kang, “Do Islamic indices provide diversification to bitcoin? A time-varying copulas and value at risk application,” *Pacific-Basin Finance Journal*, vol. 61, Article ID 101326, 2020.
- [26] P. Katsiampa, “Volatility estimation for Bitcoin: a comparison of GARCH models,” *Economics Letters*, vol. 158, pp. 3–6, 2017.
- [27] X. Ma, R. Yang, D. Zou, and R. Liu, “Measuring extreme risk of sustainable financial system using GJR-GARCH model trading data-based,” *International Journal of Information Management*, vol. 50, pp. 526–537, 2020.
- [28] H. Li, Y. Xie, J. Yang, and D. Wang, “Semiparametric estimation and panel data clustering analysis based on D-vine and C-vine,” *Mathematical Problems in Engineering*, vol. 201810 pages, 2018.
- [29] Y. K. Tse and A. K. C. Tsui, “A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations,” *Journal of Business & Economic Statistics*, vol. 20, no. 3, pp. 351–362, 2002.
- [30] T. Adrian and M. K. Brunnermeier, “CoVaR,” *The American Economic Review*, vol. 106, no. 7, pp. 1705–1741, 2016.
- [31] R. Chen, H. Chen, C. Jin, B. Wei, and L. Yu, “Linkages and spillovers between internet finance and traditional finance: evidence from China,” *Emerging Markets Finance and Trade*, vol. 56, no. 6, pp. 1196–1210, 2020.