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Research on the Coupling Mechanism between Financial Market Spectrum Risk Measurement and Copula Models Based on the Stock Index Futures Structure of ASEAN Countries

Tao Tang[1] and Yujie Ma[2,*]
[1] College of Management, GuiLin University of Aerospace Technology, Guilin, Guangxi, 541004, China
[2] School of Artificial Intelligence, Guilin University of Electronic Technology, Guilin, Guangxi, 541004, China
Corresponding authors: (e-mail: YujieMa_3016@163.com).

Abstract In this paper, a mixed-frequency time-varying Copula-CoVaR model is constructed to systematically study the spectral risk measure and risk coupling mechanism between stock index futures and spot markets. With the help of the mixed-frequency model, the volatilities of stock index futures and spot are compared and analyzed, and the residuals are converted into probability integrals to analyze the dynamic dependence by using the time-varying Copula function. The risk spillover effect between stock index futures and spot market is analyzed by CoVaR method. Based on the 1-minute high-frequency data of 4 mega-cap stocks and A50 stock index futures in ASEAN countries from 2018-2023, the macroeconomic transmission mechanism of market spectrum risk characteristics and liquidity risk is analyzed. It is found that (1) the high-frequency returns of A50 stock index futures show significant spike-thick-tail characteristics and volatility aggregation effects, and the classical RV value can effectively capture its high-frequency volatility pattern. (2) The Clayton Copula function fits the tail-dependent structure of mega-cap stocks and stock index futures optimally, indicating that there is significant tail risk spillover between markets under extreme risk events. (3) The level of regional liquidity risk is significantly affected by macroeconomic factors, with the largest liquidity volatility between the epidemic and the RCEP's entry into force, and the risk profile improving after the RCEP's implementation but not fully recovering to the pre-epidemic level.

Index Terms asean countries, spectral risk, mixed-frequency time-varying Copula-CoVaR model, stock index futures

I. Introduction

The dependence of economic growth on finance is a fundamental phenomenon in modern economic development [1]. Against the background of increasing economic globalization, international cooperation in finance not only magnifies the scope of financial activities, but also demonstrates the role of finance in economic growth in a wider perspective [2]-[4]. Such a fact has become more and more common since the Second World War, and various forms and contents of financial cooperation have been formed among developed countries, between developed and developing countries, and among developing countries, which have positively affected national economies and even the world economy [5]-[8]. In the pattern of world economic growth, it is increasingly obvious that the regional shift of the growth pole is not only a historical fact but also a realistic trend [9].

Since modern times, the pattern of Western domination of world economic development has been the dominant trend, but after entering the 21st century the rapid increase in economic activity in the East Asian region has been recognized as the most important growth pole in the world in the 21st century [10]-[12]. Within the fast-growing East Asian region, the cooperation between China, as the fastest-growing of the world's major economies, and the ASEAN countries will become an important driving force for the sustained economic growth of the East Asian region [13]-[15]. And the existing studies on China-ASEAN financial cooperation mainly focus on the overall cooperation mechanism with ASEAN countries, financial market cooperation and cross-border financial regulatory cooperation [16], [17].

Undoubtedly, risk management is crucial for investors, and the prerequisite for risk management is risk identification and estimation [18]. The main risk measures popular today are VaR and CVaR, etc., although both of them do not take into account the risk averse attitudes of investors, so they have great shortcomings [19], [20]. Spectral risk measures are both consistent risk measures while taking into account investors' risk averse attitudes, assigning greater weights to larger losses and making up for the shortcomings of VaR and CVaR [21]-[23]. Thus, with the continuous deepening of theoretical and empirical research, it is of great significance to apply spectral risk metrics to the risk management of relevant financial institutions in ASEAN countries.

In this paper, we first construct a mixed-frequency time-varying Copula-CoVaR model framework, integrate GARCH-MIDAS model to deal with high-frequency volatility decomposition, and utilize the time-varying Copula function for evolution. Relying on the CoVaR method to quantify risk spillover, a complete chain of analysis from volatility measurement to risk spillover is realized. Based on the high-frequency trading data of SET50 index constituents and A50 stock index futures of ASEAN countries, the price volatility of stock index futures in high-frequency environment is measured. Based on the mixed-frequency time-varying Copula-CoVaR model, we analyze the market spectrum risk characteristics and the macroeconomic transmission mechanism of liquidity risk.

II. Construction of time-varying Copula-CoVaR model for mixing frequency

II. A. Copula Model Setting and Dependency Measures

Copula refers to a function that "connects" the joint distribution of a multivariate variable to the marginal distributions of its individual variables. A joint distribution can be decomposed into the marginal distributions of its individual variables and a Copula function, which describes the dependence structure of the variables, characterizes the correlation, and is a function that connects the joint distribution to the marginal distributions of the variables and is often referred to as the "connectivity function".

By the unconditional Sklar theorem: assume that the marginal distribution is $F_1(x_1)$ to $F_n(x_n)$. For $x_1, x_2, ..., x_n \in R$, there exists a Couple function C such that: $F(x_1, x_2, ..., x_n) = C[F_1(x_1), F_2(x_2), ..., F_n(x_n)]$, where $F(x_1, x_2, ..., x_n)$ is a joint distribution function. If the marginal distribution is continuous, then C is uniquely determined: otherwise, C is uniquely determined by the joint domain of values from $F_1(x_1)$ to $F_n(x_n)$.

The theorem gives a way to study the dependence structure of multivariate distributions without directly analyzing the marginal analysis of the variables, and furthermore, the theorem shows that the joint multivariate distribution can be determined by setting the dependence structure between the variables and the marginal distribution of each variable. For any marginal distribution function, the Copula function can be constructed: $C[F_1(x_1), F_2(x_2), ..., F_n(x_n)] = F(x_1, x_2, ..., x_n)$.

There are two main categories of Copula functions commonly used in financial analysis, ellipsoidal and Archimedean. Ellipsoidal Copula functions are mainly multivariate normal Copula and multivariate t-Copula. Archimedean Copula commonly used are multivariate Gumbel Copula, Clayton Copula, Frank Copula function.

The multivariate normal Copula distribution function and probability density function are respectively:

$$C(u_1, u_2, ..., u_n; \rho) = \phi_\rho(\phi^{-1}(u_1), \phi^{-1}(u_2), ..., \phi^{-1}(u_n)) \tag{1}$$

$$c(u_1, u_2, ..., u_n; \rho) = |\rho|^{-\frac{1}{2}} \exp\left[-\frac{1}{2} X^{-1}(\rho - I) X\right] \tag{2}$$

where ρ is a symmetric positive definite matrix with diagonal element 1, $|\rho|$ is the determinant value of the matrix ρ; $\phi_\rho(\cdot, \cdots, \cdot)$ is the standard n Gaussian distribution function with an correlation matrix of ρ, and $\phi^{-1}(\cdot)$ is the inverse function of the standard n meta-Gaussian distribution function; $X = (x_1, x_2, ..., x_n)', x_i = \phi^{-1}(u_i), i = 1, 2, ..., n$, I is the unit matrix.

The multivariate t-Copula distribution function and the probability density function are respectively:

$$\begin{aligned} C(u_1, u_2, ..., u_n; \rho, v) &= T_{\rho,v}(T_v^{-1}(u_1), T_v^{-1}(u_2), ..., T_v^{-1}(u_n)) \\ &= \int_{-\infty}^{T_v^{-1}(u_1)} \int_{-\infty}^{T_v^{-1}(u_2)} \cdots \int_{-\infty}^{T_v^{-1}(u_n)} \frac{\Gamma(\frac{v+n}{2}) |\rho|^{-\frac{1}{2}}}{\Gamma(\frac{v}{2})(v\pi)^{\frac{n}{2}}} (1 + \frac{1}{v} X' \rho^{-1} X)^{\frac{v+n}{2}} dx_1 dx_2 \cdots dx_n \end{aligned} \tag{3}$$

$$c(u_1, u_2, ..., u_n; \rho, v) = |\rho|^{\frac{1}{2}} \frac{\Gamma(\frac{v+N}{2})[\Gamma(\frac{v}{2})]^{n-1} (1 + \frac{1}{v} X' \rho^{-1} X)^{\frac{v+N}{2}}}{[\Gamma(\frac{v+1}{2})]^n \prod_{i=1}^{n} (1 + \frac{x_i^2}{v})^{\frac{v+1}{2}}} \tag{4}$$

where ρ is a symmetric positive definite matrix with diagonal element 1 and $|\rho|$ is the determinant value of the matrix ρ; $T_{\rho,v}(\cdot, \cdots, \cdot)$ is the standard n elemental t distribution function, which has a correlation coefficient matrix of ρ and a degree of freedom of v, and $T_v^{-1}(\cdot)$ is the inverse function of a function of the t distribution function $T_{\rho,v}(\cdot)$, where the degree of freedom of the unitary t distribution is v; $X=(x_1,x_2,\ldots,x_n)', x_i=\phi^{-1}(u_i), i=1,2,...,n$, I is the unit matrix.

The Archimedean Copula distribution function is expressed as:

$$C(u_1,u_2,...,u_n)=\varphi^{-1}(\varphi(u_1)+\varphi(u_2)+\cdots+\varphi(u_n)) \tag{5}$$

where $\varphi(\cdot)$ is a generating element that satisfies $\sum_{i=1}^{n}\varphi(u_i)\le\varphi(0)$, and $\varphi(1)=0$, for any $0\le t\le 1$, $\varphi(\cdot)$ is a convex function satisfying $\varphi'(t)<0,\varphi''(t)>0$ and $\varphi(\cdot)$ is a decreasing function.

In the application of Copula functions, the binary Gumbel Copula function, the Clayton Copula function, and the Frank Copula function are the three commonly used types of Archimedean Copula, which can be easily extended to the multivariate case.

The three types of Copula functions for the n element can be defined as follows:

The specific expression for the distribution function of the n element Gumbel Copula is:

$$C(u_1,u_2,...,u_n;\alpha)=\exp\left\{-\left[\sum_{i=1}^{n}(-\ln u_i)^{\frac{1}{\alpha}}\right]^{\alpha}\right\},\alpha\in(0,1] \tag{6}$$

The specific expression for the n meta-Clayton Copula distribution function is:

$$C(u_1,u_2,...,u_n;\theta)=\left(\sum_{i=1}^{n}u_i^{-\theta}-n+1\right)^{-\frac{1}{\theta}},\theta\in(0,\infty) \tag{7}$$

The specific expression for the n elemental Frank Copula distribution function is:

$$C(u_1,u_2,...,u_n;\lambda)=-\frac{1}{\lambda}\ln\left\{1+\frac{\prod_{i=1}^{n}e^{-\lambda u_i}-1}{(e^{-\lambda}-1)^{n-1}}\right\},\lambda\ne 0,N\ge 3,\lambda\in(0,\infty) \tag{8}$$

After the risk measures of individual assets are calculated, the dependence between assets should be taken into account in the risk measures of asset portfolios, which can be portrayed by the Copula function. According to Officer year, the distribution of stock returns generally do not conform to the normal distribution, but show the distribution characteristics of “sharp peaks and thick tails”.Copula function of dependence measures a variety of measures, the kendall rank is a wide range of applications of the metrics.

II. B.GARCH-MIDAS-Copula-CoVaR models

(1) Constructing the marginal distribution model

The GARCH-MIDAS model used in this paper for the return series, is set as follows:

$$r_{i,t}=\mu+\sqrt{\tau_t g_{i,t}}\varepsilon_{i,t},\varepsilon_{i,t}\sim iid(0,1) \tag{9}$$

where the volatility of the return series is decomposed into a low-frequency long-run component τ_t and a high-frequency short-run component $g_{i,t}$, and set the short-run component $g_{i,t}$ to obey a GJR-GARCH(1,1) process, and the long-run component τ_t to be the MIDAS filtering equation subject to the realized volatility RV_t and the macroeconomic variables X_t influence the MIDAS filtered equation.

$$g_{i,t}=(1-\alpha-\gamma/2-\beta)+(\alpha+\gamma\cdot|_{(r_{i,1},t<0)})\frac{(r_{i-1,t}-\mu)^2}{\tau_t}+\beta g_{i-t,t} \tag{10}$$

$$\log\tau_{i,t}=m+\theta_R\sum_{j=1}^{K}\varphi_j(\omega_1,\omega_2)RV_{t-j}+\theta_X\sum_{j=1}^{K}\varphi_j(\omega_1,\omega_2)X_{t-j} \tag{11}$$

$$RV_t=\frac{1}{N}\sum_{i=1}^{N}(r_{i,t})^2 \tag{12}$$

where $\varphi_j(\omega_1,\omega_2)$ is the weight equation for the Beta-type lagged variable and K is the maximum lag order of the form:

$$\varphi_j(\omega_1,\omega_2)=\frac{(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}}{\sum_{i=1}^{K}(i/K)^{\omega_1-1}(1-i/K)^{\omega_2-1}} \tag{13}$$

(2) Time-varying Copula Model

The correlation coefficients of the time-varying Gaussian Copula and the time-varying tCopula used in this paper ρ are evolved based on the DCC(1, 1) process to form the DCC-Gaussian-Copula and DCC-t-Copula models. The evolution equations are as follows:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha z_{t-1} z_{t-1}^{\bullet} + \beta Q_{t-1} \tag{14}$$

$$\rho_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{15}$$

where $\bar{Q}$ is the covariance matrix of the normalized residual series, and Q_t^* is the square matrix whose diagonal elements are the square root of Q_t and whose off-diagonal elements are zero.

(3) CoVaR method

CoVaR can be used to measure the risk spillover effect, the conditional at-risk value of another financial market j when a financial market i is at a certain value-at-risk level at a certain moment in time at a confidence level of $1-q$:

$$Pr(r_t^i \le CoVaR_{q,t}^i \mid r_t^i \le VaR_{q,t}^i) = q \tag{16}$$

can be transformed into:

$$\Pr(r_i^i \le CoVaR_{q,i}^{i|i}, r_i^i \le VaR_{q,i}^i) = q^2 \tag{17}$$

Let $u_j = F_j(CoVaR_{q,i}^{jli}), u_i = F_i(VaR_{q,i}^i) = q$, Eq. (17) can be converted to:

$$C(u_j, u_i) = q^2 \tag{18}$$

The risk spillover value is obtained by solving and calculating the inverse function. In order to better illustrate the risk spillover effect of a risky event in the financial market i on j, the spillover conditional value at risk is defined as $\Delta CoVaR_{q,t}^{jli}$, and its expression is:

$$\Delta CoVaR_{q.i}^{jli} = CoVaR_{q.i}^{jli} - CoVaR_{q.i}^{jli} = VaR_{q.t}^{jli=VaR^o} \tag{19}$$

The value of spillover conditional risk is normalized to take into account the large variation in the size of risk spillovers due to quantitative issues:

$$\%COVaR_{q.i}^{jli} = \frac{\Delta CoVaR_{q.i}^{jli}}{CoVaR_{q.i}^{jli=VaR^{\infty}}} \times 100\% \tag{20}$$

Also, t^{-1} is the q quantile of the inverse function of the marginal distribution function:

$$VaR = \mu_{i,t} + \sigma_{i,t} t^{-1}(q) \tag{21}$$

(4) Backtesting test

In order to ensure that the model used in this paper can accurately measure the two-way risk spillover effect of stock index futures and spot, backtesting methodology to carry out a posteriori test, the construction of the “collision sequence”:

$$H_t = \begin{cases} 1, \text{if } R_t \le VaR_t \\ 0, \text{if } R_t > VaR_t \end{cases} \tag{22}$$

Assuming that the significance level is p, T is the total length of the collision sequence, and N is the number of $R_t \le VaR$, when $E[H_t] = p$ holds, then it should obey the distribution of χ^2 with degree of freedom 1:

$$LR_{uc} = -2\ln\{(1-p)^{T-N} p^N / [(1-N/T)^{T-N}(N/T)^N]\} \tag{23}$$

Further according to the independence test, under the condition that the original hypothesis is valid, it should obey the distribution χ^2 with degree of freedom 2:

$$LR_{\infty} = -2\ln[(1-p)^{T-N} p^N] + 2\ln[(1-\pi_{01})^{n_{00}} \pi_{01}^{n_{00}} (1-\pi_{11})^{n_{10}} \pi_{11}^{n_{11}}] \tag{24}$$

where, $n_{i,j}$ represents the number of observed i states accompanied by j states after the observed i states, $i, j = 0,1$; $\pi_{i,j} = n_{i,j} / \sum_j n_{i,j}$.

When $R_t \le VaR_t$, a new collision sequence is constructed and Backtesting test is performed following the collision sequence test above.

$$H_t^{ii} = \begin{cases} 1, \text{if } R_t^j \le CoVaR_{q,t}^{jli} \\ 0, \text{if } R_t^j > CoVaR_{q,t}^{jli} \end{cases} \tag{25}$$

At the significance level p, if the value of the calculated statistic is greater than the critical value of the χ

distribution, the original hypothesis should be rejected, and if it is not possible to reject the original hypothesis, it indicates that the model used in this paper is appropriate. In order to be more intuitive, the P-value of the test statistic is used for determination: the larger the P-value, the more accurate and independent the model is, i.e., it is reasonable and effective to use this model for risk measurement.

III. Financial Market Spectrum Risk Measurement Study on the Structure of Stock Index Futures in ASEAN Countries

III. A. Data presentation and processing

Against the backdrop of accelerating global financial market integration, ASEAN countries, as important emerging market economies in the Asia-Pacific region, have seen their financial market linkages and risk spillover effects becoming increasingly prominent. As a core tool of the financial derivatives market, stock index futures are not only an important means for investors to hedge systemic risks, but also reflect the stability of the regional financial markets in terms of price volatility and risk characteristics. However, the stock index futures market in ASEAN countries is characterized by high-frequency trading, multi-source information shocks, and heterogeneous structure, etc. Traditional risk metrics have limitations in portraying the dynamic dependence under high-frequency mixed-frequency data and capturing the tail risk spillover effect, which are difficult to meet the risk management needs of the complex financial markets.

In this study, four large-cap stocks in the SET50 of ASEAN countries and A50, a stock index futures variety in Singapore, are selected as research objects for empirical research. Since the emergence time of these research objects is different, the 1-minute high-frequency trading data of the above research objects during the period from January 1, 2018 to December 31, 2023 is selected for the study. In order to ensure the reasonableness of the price, the 1-minute closing price of the main contract of the day is selected in each trading day as the research data.

Although there will be some noise in the 1-minute data, when the data volume is large enough, the contribution of valid information will be greater than the influence of noise. In addition, the data can be judged based on the final estimation results of the model, whether the parameter iterations converge, etc. to determine whether the data is reasonable and meets the model-related assumptions.

The inconsistency in the length of the five financial market returns is mainly due to the inconsistency in their opening and closing time intervals. Since the amount of data with inconsistent trading hours is small relative to the total number of data used in this study, its impact on the results of the study will not be too great, so the time-inconsistent data are directly removed here. In addition, there is a small portion of missing data in all of the study subjects, and the missing values are supplemented by making the missing price equal to the previous minute's price. Because the time interval of high-frequency data is very short and the degree of price change between each minute is small, the logarithmic return of the price series is scaled up by multiplying it by 100. I.e:

$$y_t = \ln(p_t / p_{t-1}) * 100 \tag{26}$$

After data processing, and after calculating the returns of several financial markets according to expression (26), the individual market return series can be obtained.

III. B. Measuring price volatility of stock index futures in a high-frequency environment

III. B. 1) Distributional Characteristics of High Frequency Prices of Equity Index Futures

First, high-frequency price returns on A50 index futures are calculated using Eviews10. Assuming that the quoted price at the k time point during the t trading day of the A50 index futures is $p_{t,k}$, the price return (rate) at that time point is $r_{t,k}$, and that $r_{t,k}$ is logarithmically first-order differenced, while the value of the logarithmically differenced value is scaled up by a factor of 100 for observational purposes.

Next, the ADF unit root test is performed on this price return series and it is found to be a smooth series, indicating that future information can be inferred and predicted from the return information of the A50 index futures at past points in time, i.e., it is feasible to measure the price volatility of the A50 index futures through historical price information.

The 5-minute high-frequency price returns of A50 index futures are shown in Figure 1. It can be seen that the A50 index futures 5-minute price returns r show large fluctuations at some time points, especially strong fluctuations between the 54,000th and 71,000th time points, which roughly corresponds to the January to December 2021 time period. Period r exhibits a volatility aggregation effect of large swings followed by one large swing and small swings followed by more small swings at many time points. This feature suggests a less linear trend in the high-frequency price changes of A50 index futures.

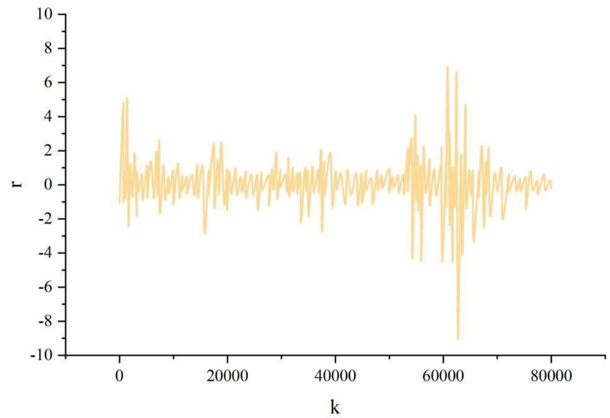

Figure 1: 5-minute high-frequency price returns for A50 index futures

In order to preliminarily determine the existence of market microstructure errors, this paper adopts a scatter plot to observe the 5-minute price return changes of A50 index futures.The 5-minute price returns of A50 index futures are shown in Figure 2. It can be seen that r always obeys a certain regularity with quite a number of intermittent points of sudden rise and fall, which tend to be concentrated in the inquiry and quotation phase of the opening, closing or closing of the market. Between the 54000th and 71000th time points, there are sharp discontinuous fluctuations in r, forming a number of "U"-shaped, "L"-shaped or "V"-shaped rapid changes in returns. This indicates that the high-frequency price returns of A50 index futures have intraday effects, and that there are phenomena related to market microstructure, such as quoting spreads and discontinuous trading in high-frequency price returns. Therefore, the interference of market microstructure noise should be excluded as much as possible in the measurement process of high-frequency price volatility of A50 index futures.

Based on the characteristics of high-frequency price returns of A50 index futures, this paper next proposes to use the high-frequency RV method to portray the price volatility of A50 index futures, in order to obtain a better measurement effect.

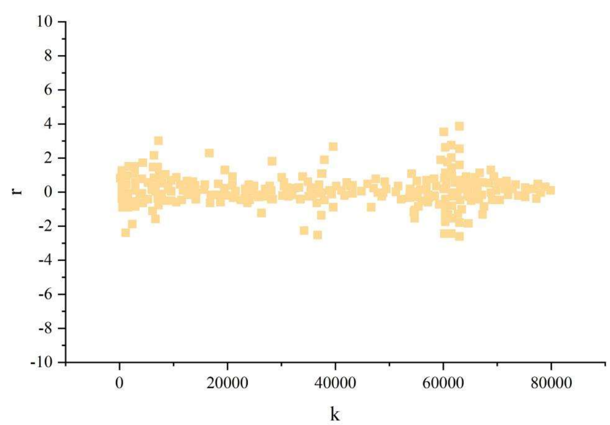

Figure 2: 5-minute price returns for A50 index futures

III. B. 2) Empirical evidence of high-frequency RV measures for stock index futures

The classical realized volatility RV_t of stock index futures on day t is calculated using the high-frequency price returns $r_{t,k}$ on A50 index futures:

$$RV_t = \sum_{k=1}^{n} r_{t,k}^2 \tag{27}$$

where n is the number of intraday time points, which is equal to the total intraday time divided by the time interval, and k is the time interval ordinal, i.e., the time frequency. It has been well established that this estimate converges to the integral fluctuation as long as the frequency of the value of the return is taken high enough, i.e., when n tends to infinity, and Eq. (27) is an unbiased estimator of the integral fluctuation. As can be seen from Eq. (27), the high-frequency RV method has model-free and parameter-free characteristics, and its mathematical function expression is very simple, which overcomes the shortcomings of the traditional historical volatility measures with many constraints and difficult parameter estimation. In order to distinguish it from the other improved RV models below, the RV expressed in equation (27) is referred to as the classical RV model in this paper.

The classical RV value of A50 index futures on day t is calculated and shown in Fig. 3. A50 index futures show some price volatility before the 1000th day of initial listing and trading, with the highest value of RV exceeding 20 at one time, and then the volatility gradually diminishes and tends to be stable. Roughly between the 1400th and 1900th day, A50 index futures experienced a second large fluctuation, and the highest RV value exceeded 90 for the first time.

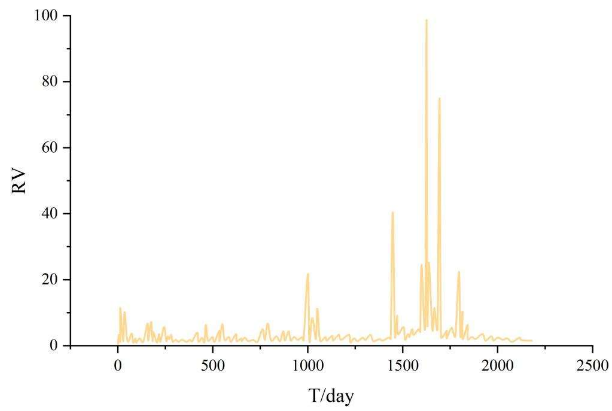

Figure 3: Classical RV values for A50 index futures

III. C. Spectral Risk Measurement for Mixed-Frequency Time-Varying Copula-CoVaR Models

III. C. 1) Parameter estimation

The GARCH-MIDAS model is used to model the intraday return series and the Copula-CoVaR model is used to study the effect of mega-cap stocks on the volatility of the stock index:

$$
\begin{aligned}
&R_{nt} = u_{nt} + \varepsilon_{nt} \quad n = 1,2, t = 1,\cdots T \\
&\varepsilon_{nt} = h_{nt}^{1/2}\xi_{nt} \\
&h_{nt} = \omega_n + \alpha\varepsilon_{n(t-1)}^2 + \beta h_{n(t-1)} \\
&(\xi_{1t}, \xi_{2t}) \mid I_{s-1} \sim C(T_{s_1}(\xi_{1t}), T_{s_2}(\xi_{2t}) \mid I_{t-1}) \\
&R_{nt} = \alpha R_{n(t-1)} + \varepsilon_{nt} \quad n = 1,2, t = 1,\cdots T \\
&\varepsilon_{nt} = h_{nt}^{1/2}\xi_{nt} \\
&h_{nt} = \omega_{nt} + \alpha\varepsilon_{n(t-1)}^2 + \beta h_{n(t-1)} \\
&(\xi_{1t}, \xi_{2t}) \mid I_{t-1} \sim C(T_{s_1}(\xi_{1t}), T_{s_2}(\xi_{2t}) \mid I_{t-1}
\end{aligned}
\tag{28}
$$

The above equation $T_{r_1}(.), T_{t_2}(.)$ obeys the following distribution: $\sqrt{\frac{v_1}{v_1-2}}\xi_{1t} \mid I_{t-1} \sim t(v_1), \sqrt{\frac{v_2}{v_2-2}}\xi_{2t} \mid I_{t-2} \sim t(v_2)]$.

And then, the Copula function of Gumbel, Clayton, and Frank is used for parameter estimation. The four mega-cap stocks are numbered as X1~X4, and the estimated values of Copula function of the four mega-cap stocks with SET50 and the estimated values of Copula function of the four mega-cap stocks with A50 are shown in Table 1 and Table 2, respectively. The tail correlation of the return series of X1 and X2 among the ultra-large-cap stocks with SET50 and A50 indices can be described by Gumbel function. All 4 ultra-large cap stocks, on the other hand, cannot be portrayed by the Frank model. The tail correlation of the return series of the four mega-cap stocks to the SET50 index and the tail correlation of the return series of X2 to the A50 index can be well modeled by the Cayton-Copula function for the day-ahead data test.The Clayton-Copula function is more effective than the Frank-Copula function in modeling the tail correlation of the return series of all the four mega-cap stocks to the A50 index. Tail correlation is more effective. The results suggest that if there is an extreme event such as a sustained shock downturn in the ASEAN stock market, the market risk of stock index futures will be further enhanced due to the existence of the correlation between the mega-cap stocks and the stock index.

Table 1: Estimates of the Copula function for four super-large-cap stocks and SET50

Stock symbol and index name	Name	Parameters	Statistic M
X1-SET50	Gumbel	0.5998(0.041)	95.4864
	Clayton	0.5176(0.032)	328.3756
	Frank	0.9956(0.045)	253.6863
X2-SET50	Gumbel	0.4836(0.021)	98.3865
	Clayton	0.6937(0.040)	157.3863
	Frank	1.2058(0.042)	592.5397
X3-SET50	Gumbel	0.5187(0.031)	144.2875
	Clayton	0.8558(0.052)	62.5873
	Frank	1.5786(0.043)	130.2764
X4-SET50	Gumbel	0.6936(0.022)	142.5876
	Clayton	0.9237(0.031)	40.1873
	Frank	1.6035(0.062)	146.0387

Table 2: Estimates of the Copula function for four super-large-cap stocks and A50

Stock symbol and index name	Name	Parameters	Statistic M
X1-A50	Gumbel	0.7846(0.044)	104.4876
	Clayton	0.4903(0.029)	375.2897
	Frank	0.9902(0.043)	250.0481
X2-A50	Gumbel	0.6567(0.033)	92.5876
	Clayton	0.6903(0.031)	132.2754
	Frank	1.1573(0.045)	195.0395
X3-A50	Gumbel	1.6973(0.044)	/
	Clayton	0.3635(0.021)	60.0385
	Frank	0.4038(0.043)	147.3865
X4-A50	Gumbel	1.6387(0.033)	/
	Clayton	0.9904(0.026)	41.0473
	Frank	1.8956(0.027)	104.2755

III. C. 2) Liquidity risk measurement

For the calculation of the value of the overall regional liquidity risk level, this paper uses the value of the liquidity risk level of each country in the region to obtain a linearly weighted calculation. Let the value of liquidity overall risk level $L = W_1^* L_1 + W_2^* L_2 + W_3^* L_3 + W_4^* L_4 + W_5^* L_5$. Where $L_n = \ln(L_t^n) - \ln(L_{t-1}^n)$, L_t is the interbank lending rate, IBOR, of a country that can represent the level of the country's money market interest rate on t, and W_n is the liquidity risk weight of each country. For the selection of liquidity risk weights, this paper first refers to the general method of setting W_n as the average equal weight, and the weights of liquidity risk of the five countries are all set to 1/5. In addition, considering that different countries have different impacts in systemic risk spillover events, liquidity risk is mainly transmitted and spread within the region from the channels of trade, investment, and external finance, and the liquidity risk situation of a country or region is not the same as that of the other countries. The liquidity risk situation of a country or region is also inevitably closely related to the overall economic and financial environment. Therefore, this paper uses the GDP of five countries as the basis for five countries to reallocate liquidity risk weights, selects the GDP of the five countries to be summed up, and sets the proportion of the summed GDP of each country to the total GDP of the five countries during the study period as the liquidity weight of that country. The GDP data is obtained from the World Bank database, and the ASEAN regional liquidity risk value is calculated using these weights. The change in the regional liquidity risk level is shown in Figure 4, where real1 indicates under the general methodology setting and real2 indicates under the weighting setting. It can be seen that the liquidity fluctuation is the highest during the period between the outbreak of the epidemic and the entry into force of the RCEP agreement, and the overall regional liquidity risk level has the highest value, while the liquidity risk situation becomes slightly better after the entry into force of the RCEP agreement, but it does not go back to the smoothest state before the outbreak of the epidemic.

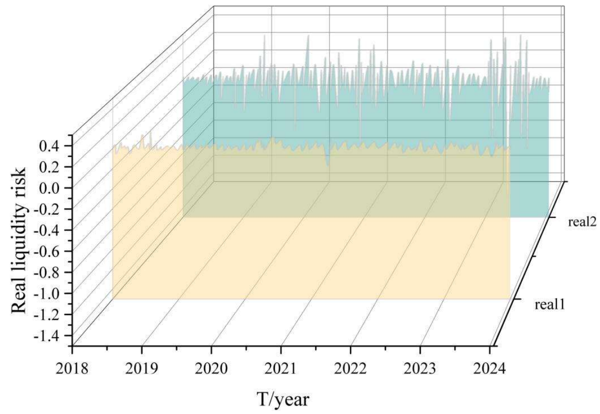

Figure 4: Changes in regional liquidity risk levels

In order to present a clearer picture of the overall liquidity risk situation in the region at this point in time, this paper constructs a regional liquidity risk indicator similar to the quarterly indicator value as shown in Figure 5.Quaterline1 shows the indicator value situation under the first liquidity risk weight setting, and Quaterline2 shows the indicator value situation under the second liquidity risk weight setting. The trend of indicator value changes under the two risk weight settings is basically the same. It can still be observed that the liquidity risk level is at its highest in the period from 2020 to 2021, and also in the mid- to late 2022. The liquidity risk level before 2020 is the smallest and has a particularly small variation.

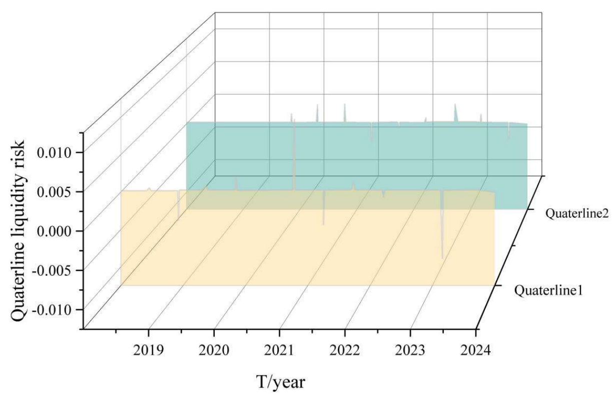

Figure 5: Regional liquidity risk indicators for quarterly index values

IV. Conclusion

This paper focuses on the coupling mechanism of spectral risk measure and Copula model in the stock index futures market of ASEAN countries, and systematically analyzes the characteristics of market volatility, dependence structure, and risk spillover effects.

First, the high-frequency returns of the A50 stock index futures show sharp discontinuous fluctuations between the 54,000th and 71,000th time points, forming a number of “U”-shaped, “L”-shaped, or “V”-shaped returns. A50 index futures showed some price volatility before the 1000th day of initial listing and trading, with the highest value of RV exceeding 20 at one time, after which the volatility gradually weakened and leveled off. Roughly between the 1400th and 1900th day, A50 index futures experienced a second large fluctuation, with the highest RV value exceeding 90 for the first time.

Second, the Clayton-Copula function is more effective than the Frank-Copula function in portraying the tail correlation of the return series of all four mega-cap stocks on the A50 index, suggesting that there is a significant tail risk spillover between markets under extreme risk events.

Third, the regional liquidity risk level is significantly affected by macroeconomic factors, with the highest liquidity volatility and the highest overall regional liquidity risk level during the period from the outbreak of the epidemic to the entry into force of the RCEP agreement, while the liquidity risk situation has slightly improved after the entry into force of the RCEP agreement, but it has not returned to the smoothest state before the outbreak of the epidemic.

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