Dependence Structure and Extreme Risk Spillover Analysis in RCEP Countries

Yucui Li

A Thesis Submitted in Partial Fulfillment of Requirements for
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การวิเคราะห์โครงสร้างความสัมพันธ์และความเสี่ยงสุดขีดในประเทศสมาชิก RCEP

วิทยานิพนธ์
ของ
Yucui Li

เสนอต่อมหาวิทยาลัยมหาสารคาม เพื่อเป็นส่วนหนึ่งของการศึกษาตามหลักสูตร
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The examining committee has unanimously approved this Thesis, submitted by Ms. Yucui Li , as a partial fulfillment of the requirements for the Doctor of Philosophy Statistical Management Science at Mahasarakham University

Examining Committee

....Chairman
(Assoc. Prof. Manad Khamkong , Ph.D.)

....Advisor
(Assoc. Prof. Piyapatr Busababodhin , Ph.D.)

....Co-advisor
(Supawadee Wichitchan , Ph.D.)

....Committee
(Asst. Prof. Sujitta Suraphee , Ph.D.)

....External Committee
(Asst. Prof. Wuttichai Srisodaphol , Ph.D.)

Mahasarakham University has granted approval to accept this Thesis as a partial fulfillment of the requirements for the Doctor of Philosophy Statistical Management Science

....
(Prof. Pairot Pramual , Ph.D.)
Dean of The Faculty of Science

....
(Prof. Anongrit Kangrang , Ph.D.)
Acting Dean of Graduate School

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AUTHOR Yucui Li
ADVISORS Associate Professor Piyapatr Busababodhin , Ph.D.
Supawadee Wichitchan , Ph.D.
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ABSTRACT

This study investigates the dependence structure and extreme risk spillover effects among RCEP countries using Vine Copula and CoVaR methods. First, we adopted the framework of dependence structure and risk spillover, conducted simulation experiments to validate the effectiveness of Vine Copula in capturing asymmetric dependence and CoVaR in measuring extreme risk spillovers. Subsequently, we analyze the impact of the RCEP on the dependence structure of its member countries and the risk transmission mechanisms using stock index of RCEP countries and China's industry index. The findings reveal that: (1) The implementation of the RCEP has significantly altered the dependence structure among its members, interdependence structure of the markets has shown a multipolar characteristic, transitioning from a structure dominated by South Korea to a multipolar one centered around South Korea and Australia.Two primary risk spillover paths: China → Korea → Japan → Singapore → Thailand → Malaysia → Philippines → Vietnam → Indonesia; And Singapore → New Zealand → Australia → Korea → Japan → Thailand → Philippines → Vietnam → Indonesia. (2) Under the ESG framework, China's industry structure revolves around the ESG benchmark index, where C-Vine Copula confirms ESG's central role, D-Vine illustrates the upstream positions of agriculture, manufacturing, and consumer industries, and R-Vine depicts the complex interdependencies among sectors. Furthermore, CoVaR analysis identifies the key risk spillover pathways. This study enhances the understanding of financial and industrial dependence within RCEP countries and provides valuable insights for optimizing regional economic cooperation, strengthening supply chain resilience, and formulating ESG-driven risk management strategies.

Keyword : RCEP, dependence structure, extreme risk spillover, Vine Copula, CoVaR

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Introduction

1.1 Research Background

The official signing and implementation of the Regional Comprehensive Economic Partnership (RCEP) on November 15, 2020, marked the establishment of the world's largest free trade area. The agreement encompasses 15 member countries: China, the ten ASEAN nations, as well as Japan, South Korea, Australia, and New Zealand. Collectively, these countries account for approximately 30% of the world's total economic output and population, making RCEP a significant milestone in global economic integration. Through the reduction of tariffs and non-tariff barriers, simplification of cross-border trade, enhanced intellectual property protection, and promotion of trade facilitation and investment liberalization, RCEP injects new momentum into economic cooperation across the Asia-Pacific region.

The agreement not only fosters deeper integration of regional supply and value chains but also accelerates the reshaping of global supply networks. As the largest free trade zone globally, RCEP's policy benefits enable member states to capitalize on economies of scale and strengthen the region's influence in the global economic landscape. However, the rapid pace of economic globalization has led to an increased interconnection between regional economies and financial markets, creating more complex dependencies within these systems.

Against the backdrop of growing global uncertainty—exemplified by the COVID-19 pandemic (Baker, S.R,2020), geopolitical tensions (Reboredo, J. C), and climate change (UNEP (2021) —potential risk spillovers among RCEP countries' financial markets and industries have become a significant challenge to regional economic stability and sustainable development (Baker, S.R,2020). Financial or economic fluctuations in one member state can quickly transmit to others via interconnected networks, triggering systemic risks that may destabilize regional supply chains and industries. This underscores the critical need for robust risk management frameworks capable of mitigating the spread of financial shocks.

Understanding and quantifying the dependencies between financial markets is essential to reducing systemic risk and enhancing economic resilience. By examining the interrelationships between countries and industries, the ability to manage risk transmission and spillover effects in extreme scenarios is crucial for effectively responding to external shocks and ensuring rapid recovery. This has become a key objective for RCEP countries striving to strengthen economic cooperation and regional stability.

Although considerable research has been conducted on the interdependence of financial markets, studies focusing specifically on RCEP remain limited, particularly in capturing nonlinear relationships and tail dependencies, which are essential for extreme risk analysis. The application of advanced econometric tools, such as Vine Copula models and CoVaR methods, provides a flexible and powerful framework for addressing these complexities. This study aims to fill these gaps by examining the dependence structure and extreme risk spillovers within RCEP, offering valuable insights for both theoretical exploration and practical risk management. The findings are expected to contribute to expanding the field of financial risk analysis, providing policymakers and market participants with tools to enhance regional financial stability and resilience in an increasingly interconnected global economy.

1.2 Research Objectives

The implementation of RCEP has significantly impacted both member countries and the global economy. As interdependence between markets increases and industry structures become more complex, the likelihood and intensity of risk transmission through supply and value chains are also on the rise. This study, using a layered analytical framework, aims to explore the interrelationships and risk spillovers between the financial markets, industry structures, and supply chains of RCEP nations. The key research objectives are as follows:

(1) To compare and identify the volatility and dependent structural relationships among financial markets and industrial sectors. By using Copula analysis, this objective identifies and compares the dependency structures between markets and industries. By analyzing industry index data, we aim to describe the relationships between industries across RCEP member states and assess changes driven by policy shifts. At the national level, the study will focus on China, analyzing the interdependence of its industry sectors under the ESG policy framework and examining the risk transmission patterns.

(2) To explore the risk spillover path of RCEP countries and the risk transmission mechanisms among Chinese industries under the ESG framework. Based on the understanding of dependency structures, this objective calculates the risk values in the context of extreme market events. It aims to quantify the extent of risk spillovers, identify their transmission paths and mechanisms, and provide recommendations for preventing financial crises, optimizing industrial structures, and enhancing supply chain resilience.

1.3 Research Significance

(1) Promoting regional economic development and stability in national level. The implementation of RCEP has accelerated regional economic integration, but the growing interdependence between financial markets and the real economy poses new risks to stability. This study explores the interdependencies within financial markets across member countries, identifying risk spillover paths and mechanisms. It provides valuable theoretical insights for maintaining regional economic stability, addressing cross-border capital flow risks, and enhancing financial resilience. The findings will inform policy coordination efforts under multilateral economic frameworks.

(2) Optimizing industrial structure and enhancing resilience in industry level. RCEP has deepened transnational industrial cooperation, making the resilience of industries and supply chains a critical factor for regional development. By quantifying the interdependence within China's industrial sectors and analyzing risk transmission patterns, this study identifies vulnerabilities in the industrial chain and informs strategies to optimize industrial collaboration. The research will provide a scientific foundation for industrial policy formulation and contribute to the development of a competitive, risk-resilient industrial system.

(3) Enhance the anti-risk ability of the industrial chain in sector level. As industries become more interconnected, risks can rapidly spread through supply chains, leading to systemic crises. Policies like ESG can optimize supply chain interdependencies by promoting environmental responsibility, social stability, and good governance. This reduces risk spillovers from environmental, social, and managerial failures. By improving governance and sustainability, industries can mitigate the impact of external shocks, enhancing supply chain stability and resilience for long-term success.

Through a hierarchical analysis of RCEP countries, industries, and sectors, this study not only addresses regional economic development goals but also provides new theoretical and practical insights on optimizing industrial structure and strengthening supply chain resilience. Theoretically, it deepens the understanding of financial and industrial chain resilience in the context of regional economic integration and expands the use of dynamic nonlinear dependence models. Practically, it offers evidence for risk management and policy optimization, supporting financial stability, industrial development, and sustainable supply chain cooperation within RCEP member states.

1.4 Problem Statement

While RCEP aims to promote regional economic integration and market openness, its economic impact involves complex risk spillover mechanisms and interdependencies among markets. Although extensive research has been conducted on trade cooperation and economic development under the RCEP framework, the complex dynamics between financial markets and industrial structures remain underexplored. Key research gaps include:

In financial market level, existing studies primarily focus on individual market volatility, lacking a comprehensive analysis of the interdependence and risk spillover effects within the financial markets of RCEP member countries.

In industrial structure level, as the core member of RCEP, China's internal industrial interdependencies and systemic risks are insufficiently studied, particularly in terms of identifying and assessing dynamic nonlinear relationships. Understanding the resilience of industrial chains and the mechanisms of risk transmission is a critical issue to address.

To fill these gaps, this study will employ ARMA-GARCH model, Vine Copula model and CoVaR methodologies to explore the following key research questions:

(1) How do the interdependencies and dynamic characteristics of financial markets in RCEP member countries manifest?

(2) What are the risk spillover paths and transmission mechanisms among these markets.

(3) How do industries in China interdepend and risks spillover under extreme conditions in the context of ESG? Furthermore, how can the resilience of industrial and supply chains be assessed in extreme scenarios?

1.5 Research Outline

This study based on the research of scholars on dependence structures and risk management, examines the dependence structure of financial markets in RCEP countries, the interconnections and risk spillover effects within China's industrial structure, and the dynamic correlations and risk transmission processes between markets and industries. Additionally, it explores risk spillover effects under extreme conditions across financial markets and industries in different countries. The study employs the Vine Copula method to analyze dependence structures and calculates CoVaR values to assess risk spillovers under specific conditions. Furthermore, it discusses the application of dependence models in risk measurement and spillover analysis.

The research contents as follows:

Chapter 1: Introduction. This chapter introduces the research background, summarizes the research on dependence structures and risk spillover effects, analyzes the interaction of financial markets under the RCEP framework, the impact on industrial structures, and the risk contagion characteristics under extreme market conditions. It proposes combining Copula functions, Vine-Copula models, and CoVaR in the study of financial market risk spillovers.

Chapter 2: Literature Review. This chapter reviews the research on dependence structures, summarizing traditional linear dependence structure theories, nonlinear dependence structure theories based on Copula functions, and the current state of research on risk spillover effects. It explores the transmission paths and mechanisms of volatility between markets and industries, highlighting gaps in existing research.

Chapter 3: Research Methodology. Overview of Related Theoretical Models. This chapter systematically explains the principles and applications of Copula theory, Vine Copula models, and CoVaR risk measurement methods, as well as the study of risk contagion and spread under extreme conditions.

Chapter 4: Results. First, we simulate how Vine Copula captures nonlinear dependent structures under different distribution patterns, and apply the Vine Copula method to different fields. Application study 1 investigates the changes in the dependence structure of national financial markets under the implementation of the RCEP policy. It studies the stock market indices of RCEP countries using the ARMA-EGARCH model to obtain the marginal distributions of stock index returns. Based on this, a Vine-Copula model is constructed to analyze the changes in the dependence structure of stock markets before and after the implementation of the RCEP framework. Finally, the risk spillover and contagion effects of the stock markets are measured, and the CoVaR of stock market portfolios is calculated based on the R-Vine-Copula model, examining the changes in the dependence and risk spillover effects between countries before and after the agreement's implementation. Application study 2 explores the interdependencies between domestic industries in China under the ESG framework, and uses CoVaR to measure the risk spillover contagion patterns between industries under extreme conditions.

Chapter 5: Conclusion and Discussion. This chapter summarizes the key findings of the study. Based on the research on the dynamic dependence structure changes in RCEP countries' financial markets and the risk spillovers in industrial structures, it provides policy recommendations for market regulation in China and other RCEP countries. It also suggests areas for future in-depth research on market risk contagion and the resilience of supply chains and industrial chains.

1.6 Research Framework

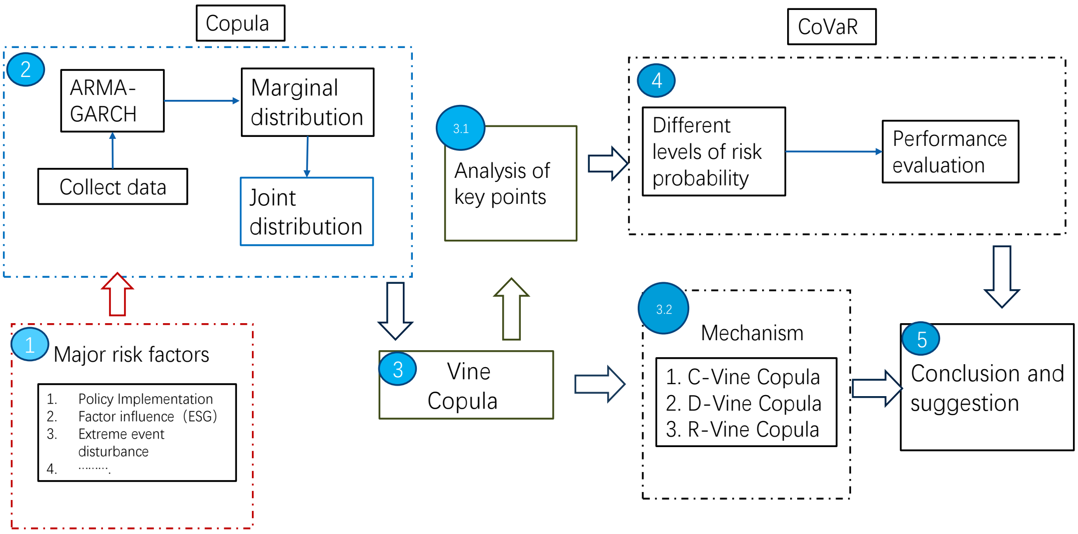


Figure 1 :The Research Framework

Chapter 2
Literature Review

In this chapter, we introduce the concepts of dependence structures, covering both linear and nonlinear dependence models, with a particular focus on the advantages of the Vine Copula model in high-dimensional dependence structure modeling. Additionally, we discuss the definition and measurement methods of risk spillovers, highlighting the application of the CoVaR method in assessing risk spillover effects in financial markets. Furthermore, we review the existing research on dependence structures and risk spillovers in financial markets, summarize the research gap, and lay the theoretical and methodological foundation for the subsequent analysis.

2.1 The Theory of Dependence Structure

Dependence structure refers to the interrelationships or dependencies between two or more random variables, serving as a critical functional measure of market dependency. Such relationships may manifest as correlations, dependencies, and risk transmission mechanisms among markets. The dependence structure not only characterizes the interconnections between different variables or assets but also determines the propagation pathways of systemic risks. Consequently, understanding the dependence relationships among variables is of paramount importance for risk forecasting, decision-making, and market stability assessment. The theory of dependence structure is widely applied in fields such as financial markets, risk management, and supply chain research.

In the domain of risk management, a thorough analysis of dependence relationships among assets helps to uncover market resonance effects during financial crises, risk contagion mechanisms under extreme market conditions, and co-movement phenomena of financial products. In economic research, the study of dependence structures facilitates the exploration of mutual influences among industries and nations. Particularly in the context of globalization, research on dependence structures enables a deeper understanding of risk propagation mechanisms within supply chains and industrial networks.

Currently, research on dependence structures primarily focuses on two types of models: linear dependence models and nonlinear dependence models.

2.1.1 Linear Dependent Model

Linear dependent models mainly include linear correlation coefficient method, ARIMA model, Granger causality test, Cointegration test.

2.1.1.1 Linear Correlation Coefficient

Linear correlation coefficients are statistical measures used to quantify the strength and direction of a linear relationship between two variables. More commonly used are Pearson correlation coefficient, Spearman's rank correlation, Kendall’s τ.

Pearson Correlation Coefficient (1896) is a statistic used to measure the strength and direction of the linear relationship between two variables, and its value ranges from -1 to 1. A value closer to -1 or 1 indicates a stronger linear relationship between variables, and a value closer to 0 indicates a weaker linear relationship.

For a set of data(X_1, Y_1),(X_2, Y_2),...,(Xn, Yn), whose correlation coefficient $\rho_{X,Y}$ is usually calculated by the Pearson correlation coefficient formula:

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y}, \tag{2.1}$$

where $Cov(X,Y)$ is the covariance of X and Y, indicating the degree to which X and Y change simultaneously. σ_X and σ_Y are the standard deviations of X and Y, respectively, indicating the degree of dispersion of X and Y. The formula of $Cov(X,Y)$ as follows:

$$Cov(X,Y) = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y}). \tag{2.2}$$

Pearson correlation coefficient is widely used to describe and analyze the correlation between financial assets, and is a basic tool to measure the market dependence. Markowitz (1952) first proposed the mean-variance optimization framework, which establishes the modern portfolio theory by analyzing the correlation between assets to construct the optimal portfolio. Elton stressed the importance of asset correlation in risk diversification. Campbell used correlation and covariance methods to study the interaction between stock and bond markets. Forbes studied the co-movement of international stock markets, distinguishing between financial market interdependence and contagion effects.

Although the Pearson correlation coefficient is capable of measuring the strength of association between two variables and quantifying their linear dependence, it cannot establish causal relationships nor capture nonlinear dependencies. This limitation is particularly significant in financial markets, where tail dependence among asset returns is often overlooked.

To address the shortcomings of the Pearson correlation coefficient, alternative measures such as Spearman's rank correlation coefficient and Kendall's τ have been introduced. These rank-based correlation measures rely on the ordinal information of variables and are better suited for capturing nonlinear monotonic relationships. Specifically, Spearman's rank correlation evaluates the strength and direction of the association between two variables based on their ranked values, while Kendall's tau assesses the concordance of pairs of observations. Both measures provide robust tools for analyzing dependencies in scenarios where linear assumptions fail, particularly in the context of financial data characterized by complex, non-Gaussian distributions.

Spearman's rank correlation (1904) measures the monotonic relationship between two variables based on their ranks. It is calculated as:

$$\rho_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}, \tag{2.3}$$

where, $d_i = rank(X_i) - rank(Y_i)$ is the difference between the ranks of corresponding values, n is the number of observations.

Kendall's τ (1938) measures the ordinal association between two variables by considering the number of concordant and discordant pairs. It is defined as:

$$\tau = \frac{C - D}{\frac{1}{2}n(n-1)}, \tag{2.4}$$

where, C is the number of concordant pairs (pairs where the relative order of X and Y is the same), D is the number of discordant pairs (pairs where the relative order of X and Y is different), n is the number of observations.

Both Spearman's ρ and Kendall's τ are widely used to measure non-linear relationships and are particularly useful when the assumption of normality is violated.

2.1.1.2 Linear Regression

Linear regression describes the linear dependence between the dependent variable Y and the independent variable X, and quantifies this dependence by estimating the regression coefficient. The formula is as follows:

$$Y = \beta_0 + \beta_1 X + \varepsilon. \tag{2.5}$$

Where β_0 is the intercept, β_1 is the slope, and ε is the random error term.

Draper & Smith (1998) systematically introduced the linear regression model and its practical applications. Meanwhile, Longin & Solnik (2001) explored the dynamics of correlation in international stock markets, with a particular focus on linear correlations under extreme market conditions. However, linear regression relies on the assumption that the relationship between dependent and independent variables is strictly linear, and the random error term follows a normal distribution.

2.1.1.3 ARIMA Model

ARIMA (Autoregressive Integrated Moving Average Model) is a statistical model for time series analysis that combines autoregressive (AR), difference (I) and moving average (MA) components. ARIMA captures the linear-dependent nature of time series through autoregressive (AR) and moving average (MA) components. The AR component describes the linear dependence between the current value and the past value, and the MA component describes the linear relationship between the current value and the past random error. It can model and predict time series data, especially for time series with trend and seasonal components, and describe linear dependence of univariate time series.

The autoregressive part (AR) uses the past values of the time series itself to predict the current values. Assuming the sequence is yt, the autoregressive (AR) model can be expressed as:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \xi_t, \tag{2.6}$$

where ϕ_i is the autoregressive coefficient, p is the autoregressive order, and ξ is white noise.

The difference part I is used to make a non-stationary time series stationary. The trend and seasonal components are eliminated by differential calculation of the time series. The first difference is expressed as:

$$y_t' = y_t - y_{t-1}. \tag{2.7}$$

The moving average (MA) uses past prediction errors to model the current value. Assuming that the sequence is y_t, the moving average model can be expressed as:

$$y_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q}, \tag{2.8}$$

where θ_i is the moving average coefficient, q is the moving average order, and ε_t is the white noise.

The ARIMA model is usually expressed as ARIMA(p, d, q):

$$\Delta^d y_t = \phi_1\Delta^d y_{t-1} + \cdots + \phi_p\Delta^d y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q}, \tag{2.9}$$

where p is the order of the autoregressive part, d is the number of differences, q is the order of the moving average part, and Δ represents the difference operation

Box(1990) introduces the theoretical basis and application method of ARIMA model, which is a classic work in the field of time series analysis.

2.1.1.4 VAR Model

The core idea of the VAR model (Sims, C. A. ,1980) is to represent the future values of multiple time series variables as linear combinations of the past values of these variables. The dynamics of each variable depends not only on its own past values, but also on the past values of other variables. VAR describes the dynamic linear dependence between variables through the lag value of variables. Moreover, the model does not distinguish between endogenous variables and exogenous variables, but treats all variables as equivalent endogenous variables, which enables the model to capture the bidirectional linear dependence relationship at the same time. By analyzing the perturbation of the error term ϵt, the VAR model can measure how changes in one variable are transmitted to other variables through linear dependencies.

The basic form of VAR model can be expressed as:

$$Y_t = A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + u_t, \tag{2.10}$$

where Y_t is a $k \times 1$ time series vector containing k variables. A_i is the coefficient matrix of $k \times k$, representing the influence of i in the lag period. p is the order of lag. u_t is a $k \times 1$ error term vector, usually assumed to be a white noise sequence.

Through VAR model analysis, we can reveal the linear dependence between multivariate time series. By capturing the lag effect between variables, we analyze their interdependence, dynamic relationship and causal transfer effect. VAR model is widely used to study the linkage effect between different financial markets (such as stock market, bond market, foreign exchange market). Campbell (1993) used VAR model to analyze the mutual influence of stock market and bond market, and discussed the sources of volatility of stock market and bond market and their impact on long-term asset return. Hasbrouck, J. (1995) uses the VAR model to analyze the contributions to price discovery across multiple markets. Diebold, F. X., & Yilmaz, K. (2009) employs the VAR model to study return and volatility spillovers in global equity markets.

In complex environments such as financial markets and economic systems, traditional linear dependence models, are often used to capture relationships between variables. While these models can be effective for some applications, they face significant limitations. Specifically, they rely on assumptions of linearity and mean-variance analysis, which fail to account for more intricate nonlinear dependencies and extreme tail risks. As a result, they struggle to accurately represent the full range of interdependencies present in these systems. To address these limitations, nonlinear dependence models, such as Copula theory, Vine Copula, and dynamic dependence structure modeling methods, offer a more flexible and comprehensive framework. These models are capable of revealing nonlinear and tail dependence characteristics between variables under varying conditions, providing a more accurate description of complex relationships.

2.1.2 Nonlinear Dependence Model

Traditional models, like correlation coefficients, linear regression, ARIMA, and vector autoregression, typically assume that the joint and marginal distributions of market returns follow a normal distribution. However, numerous empirical studies have shown that asset returns often deviate from normality, exhibiting characteristics such as leptokurtosis, heavy tails, volatility clustering, and asymmetry. Furthermore, the interdependence between different markets often displays significant tail dependence and asymmetry, which traditional models fail to capture. To address these challenges and better represent the complexities of financial markets, nonlinear dependence models are essential. These models offer a more accurate and nuanced description of the relationships between markets, particularly in the presence of non-normal distributions and extreme events.

2.1.2.1 GARCH Model

In the 1950s, Modern Portfolio Theory (MPT) was introduced by Markowitz(1952), emphasizing that portfolio diversification can reduce risk. MPT relies on the covariance matrix and correlation coefficients to optimize portfolios but overlooks the nonlinear dependencies in financial markets.

Subsequently, in the 1980s, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model (1986) was proposed to capture the volatility clustering effect in financial market. The GARCH family, which includes models like ARCH (AutoRegressive Conditionally Heteroscedastic model), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), EGARCH (Exponential GARCH), and GJR-GARCH, was developed to better model and forecast volatility in financial markets. These models focus on capturing time-varying volatility and the phenomenon of volatility clustering, where periods of high volatility tend to follow high volatility and low volatility follows low volatility.

Engle (1982) introduced the ARCH model (AutoRegressive Conditionally Heteroscedastic model), which accurately captures the characteristics of financial time series and represents the changing volatility over time as a statistical model. The core idea of the ARCH model is that volatility is conditionally heteroskedastic, meaning that the size of volatility depends on past levels of volatility. The form of the model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2, \tag{2.11}$$

where σ^2 is the volatility at time, ε_{t-i} is the residual at time $t-i$ (the difference between observed and predicted values), and α_0 and α_i are the model parameters that control the impact of past residuals.

Bollerslev(1986) extended the ARCH model and introduced the GARCH (Generalized AutoRegressive Conditional Heteroscedasticity model). This expansion incorporated the concept of past volatility, enhancing the model's flexibility to better describe logarithmic returns and comprehensively capture long-term financial data volatility trends.

The GARCH model is used to analyze the volatility characteristics in time series data, especially the volatility concentration in financial market data. The traditional time series model assumes that the volatility of data is constant, while the GARCH model describes the change of volatility by capturing conditional heteroscedasticity, which is more suitable for modeling the nonlinear dependence of financial data. In the financial market, volatility is often not constant, but presents a phenomenon of agglomeration, that is, large fluctuations tend to follow large fluctuations, and small fluctuations tend to follow small fluctuations. The GARCH model assumes that the volatility (variance) of the current period is dependent on the volatility of previous periods, and through autoregressive and moving average components, the GARCH model is able to dynamically adjust the prediction of volatility, effectively capturing this feature. Cappiello et al. (2006) applied the GARCH model to assess market correlations and volatility spillovers.

The GARCH model consists of two parts, the mean equation and the variance equation.

Mean equation part describes the mean part of a time series, usually in the form of an ARMA model.

$$y_t = \mu + \varepsilon_t, \tag{2.12}$$

where ε_t is white noise and follows a normal distribution N(0, σ_t^2).

Variance equation part describes the conditional heteroscedasticity of the time series, the volatility part.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{2.13}$$

where, $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$ to ensure the stability of the model.

The GARCH model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \alpha_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-i}^2,$$
$$\alpha_t = \sigma_t \varepsilon_t. \tag{2.14}$$

However, the GARCH model is difficult to measure the asymmetry of income volatility and leverage effect in financial assets. Bollerslev (1991) extended the GARCH model. He believed that the volatility increase caused by market decline was more obvious, and therefore proposed the EGARCH model to capture the asymmetric effect of volatility. Engle (1993) applied the EGARCH model to solve the problem of symmetric treatment of volatility shocks. The EGARCH model allows volatility to react differently to positive and negative news shocks, allowing it to more accurately capture asymmetric volatility in financial time series. The expression of EGARCH model is as follows:

$$ln\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \left(\mathcal{E}_{t-i} - \Upsilon_i \mathcal{E}_{t-i}\right) + \sum_{j=1}^{q} \beta_j \, log(\sigma_{t-i}^2). \tag{2.15}$$

Glosten (1993) extended the GJR-GARCH model by introducing leverage effect to capture the effect of negative returns on volatility with additional parameters. The GJR-GARCH model (Glosten-Jagannathan-Runkle GARCH) is an extension of the GARCH model designed to capture the asymmetric effect in financial time series, where positive and negative shocks have different impacts on volatility. This is also known as the leverage effect.

The Conditional Variance Equation as follow:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta h_{t-1}, \tag{2.16}$$

where h_t is conditional variance (squared volatility at time t). ω is constant term, representing the long-run variance level.α is effect of lagged squared residuals (ARCH effect). β is effect of lagged conditional variance (GARCH effect). γ is captures the additional impact of negative shocks (asymmetry term). ε_{t-1}^2 is lagged squared residual (shock). I_{t-1} is indicator function.

$$I_{t-1} = \begin{cases} 1, if\ \varepsilon_{t-1} < 0 (negative\ shock) \\ 0, if\ \varepsilon_{t-1} \geq 0 (positive\ shock). \end{cases} \tag{2.17}$$

In summary, GARCH models can be adapted to specific use cases (intraday volatility, long memory) by tweaking lag orders, distribution assumptions, or using extensions like long-memory GARCH or regime-switching GARCH. As they provide a more accurate reflection of volatility dynamics compared to traditional models that assume constant variance.

2.1.2.2 Copula

GARCH models are used to capture the conditional heteroskedasticity of individual time series. when we need to modeling multivariate nonlinear dependence, Copula can help. The word “Copula” derives from the Latin verb “copulare” and means to “bond” or “tie.” Copula is a function that links the marginal distributions of individual variables to form their joint distribution. It used to describe the dependence relationship between random variables. The copula approach was introduced by Sklar (1959), it is a method used to construct multivariate distribution, which describes the dependency structure between variables by separating the edge distribution from its joint distribution, and is widely used to describe the nonlinear tail dependency structure of financial markets. Unlike traditional correlation analysis, Copula functions can capture nonlinear and asymmetric dependencies between variables, especially when the marginal distribution does not need to be normal. The primary strength of Copula lies in its ability to capture the interdependence among variables, enabling the computation of joint probabilities without being affected by the marginal tendencies of the variables in question. Essentially, it seamlessly merge several univariate marginal distributions to generate their associated joint distribution. In the mid-1990s Copula have been used as a tool for modelling dependencies between assets in empirical finance. Recently, the field of Copula has seen rapid advancements, demonstrating significant potential in analyzing multivariate joint distributions and conducting multivariate frequency assessments.

Sklar's Theorem: Let F be a bivariate distribution with marginal distributions F_1, F_2. There exists a two-dimensional Copula $C(\cdot,\cdot)$, such that:

$$\forall(x_1,x_2) \in R^2 : F(x_1,x_2) = C(F_1(x_1),F_2(x_2)). \tag{2.18}$$

If F_1 and F_2 are continuous, the Copula $C(\cdot,\cdot)$ is unique. Since C_Y is the cumulative distribution function of $\{F_{Y1}\ (Y1),\ldots,F_{Yd}\ \ (Yd)\}$,

$$\begin{aligned} C_Y(u_1,\ldots u_d) &= P\{F_{Y_1}(Y_1) \le u_1,\ldots,F_{Y_d}(Y_d) \le u_d\} \\ &= P\{Y_1 \le F_{Y_1}^{-1}(u_1),\ldots,Y_d \le F_{Y_d}^{-1}(u_d)\} \\ &= F_Y\{F_{Y_1}^{-1}(u_1)\ \ldots,F_{Y_d}^{-1}(u_d)\}. \end{aligned} \tag{2.19}$$

Using this theorem, flexible multivariate distributions can be constructed from d-dimensional copulas. Joe (1996) initially introduced Pair-copula constructions (PCC) functions to construct joint distributions for multivariate variables. We can represent a density $f\ (x_1,\ldots,x_d)$ as a product of pair copula densities and marginal densities.

For d = 2, we can immediately derive expressions for the conditional density and distribution functions, which are needed later. The conditional density $f_{1|2}$ and distribution function $F_{1|2}$ can be expressed as:

$$\begin{aligned} f_{1/2}(x_1|x_2) &= c_{12}(F_1(x_1), F_2(x_2))f_2(x_2), \\ F_{1|2}(x_1|x_2) &= \frac{\partial}{\partial F_2(x_2)} C_{12}(F_1(x_1), F_2(x_2)), \\ &= \frac{\partial}{\partial v} C_{12}(F_1(x_1), v)/_{v=F_2(x_2).} \end{aligned} \tag{2.20}$$

For example, d = 3 dimensions. One possible decomposition of $f\ (x_1, x_2, x_3)$ is:

$$\begin{aligned} f(x_1, x_2, x_3) &= f_{3|12}(x_3|x_1, x_2) \cdot f_{2|1}(x_2|x_1) \cdot f_1(x_1), \\ f_{2|1}(x_2|x_1) &= c_{12}(F_1(x_1), F_2(x_2)) \cdot f_2(x_2), \\ f_{3|12}(x_3|x_1, x_2) & \\ &= c_{13|2}(F_{1|2}(F_{1|2}(x_1|x_2), F_{3|2}(x_3|x_2)) \cdot f_{3|2}(x_3|x_2), \\ f_{3|2}(x_3|x_2) &= c_{23}(F_2(x_2), F_3(x_3)) \cdot f_3(x_3). \end{aligned} \tag{2.21}$$

After rearranging the terms, the joint density can be written as:

$$\begin{aligned} f(x_1, x_2, x_3) &= f_3(x_3) \cdot f_2(x_2) \cdot f_1(x_1) \quad \text{（marginals）} \\ &\times c_{12}(F_1(x_1), c_{23}(F_2(x_2)F_3(x_3)) \quad \text{(unconditional pairs)} \\ &\times c_{13|2}(F_{1|2}(x_1|x_2), F_{3|2}(x_3|x_2)) \quad \text{(conditional pairs).} \end{aligned} \tag{2.22}$$

There are several types of copulas, broadly categorized into three main families based on their characteristics and flexibility.

Table 1:Type of Copula Family

Family	Copula name	Copula Function	Parameter	Tail Dependence
Elliptical	Gaussian	$\phi_{\rho}(\phi^{-1}(u_1), \phi^{-1}(u_2))$	$\theta \in (-1, 1)$	No Tail
	t-Copula	$t_{v,\rho}(t_v^{-1}(u_1), t_v^{-1}(u_2))$	$v, \rho > 0$	Both Tails
Archimedean	Joe	$1-(1-u)^{\theta}+(1-v)^{\theta}$	$\theta > 1$	Upper
	Clayton	$[max(u_1^{-\theta}+u_2^{-\theta}-1,0)]^{-1/\theta}$	$\theta > 0$	Lower
	Frank	$-\frac{1}{\theta}log[1+\frac{(e^{-\theta_u}-1)((e^{-\theta_v}-1)}{e^{-\theta}-1}$	$\theta \neq 0$	Upper
Extreme	Gumbel	$exp(-[(-lnu_1)^{\theta}+(-lnu_2)^{\theta}]^{1/\theta})$	$\theta \geq 1$	Upper
	Galambos	$exp(-((-lnu_1)^{-\theta}+(-lnu_2)^{-\theta})^{-\frac{1}{\theta}})$	$\theta > 0$	Upper
	Husler-Reiss	$exp(-\phi(\frac{\lambda}{2}+\frac{ln(-lnu_1)-ln(-lnu_2)}{\lambda}))$	$\lambda > 0$	Upper

Different types of copulas capture various dependency structures in financial markets and risk modeling. Elliptical copulas, including Gaussian Copula and t-Copula, are used to model dependencies between variables that follow elliptical distributions. Gaussian Copula assumes a normal dependency structure but lacks tail dependence, whereas t-Copula extends this by incorporating both upper and lower tail dependence, making it more suitable for risk analysis. Archimedean Copulas includes various types such as Joe Copula, Clayton Copula, and Frank Copula, which are useful for modeling different types of asymmetric dependencies (Nelsen, 2006). Clayton Copula is effective in modeling lower tail dependence, capturing extreme co-movements during financial crises, while Joe Copulas focus on upper tail dependence, useful for analyzing market bubbles. Frank Copula, on the other hand, does not exhibit tail dependence and is often used when the dependency structure is symmetric. Meanwhile, Gumbel, Galambos and Hüsler-Reiss Copulas, as extreme value copulas, are particularly useful for modeling extreme co-movements, with Galambos emphasizing strong upper tail dependence and Hüsler-Reiss capturing more general extreme dependencies (Genest 2007). Each copula provides unique advantages, allowing for flexible modeling of nonlinear dependencies and extreme risk spillovers in financial markets.

Embrechts (2002). discussed the application of Copulas in risk management, with a particular focus on the properties and limitations of dependence structures. Patton (2006) introduced the dynamic Copula model into the financial field to analyze time-varying dependencies and revealed asymmetric tail dependence characteristics through the Copula framework. In a subsequent review, Patton (2012) summarized the applications of Copula models in economic time series, emphasizing the development of dynamic Copula models. Additionally, Genest (2007) explored the use of extreme value Copulas, particularly in capturing tail dependencies in extreme scenarios.

2.1.2.3Vine-Copula

Traditional Copula models are primarily designed for two-dimensional data, which limits their applicability in complex, high-dimensional dependency structures. As financial markets, risk management, and supply chain networks often involve multiple interdependent variables, the need for a more flexible approach became evident.

To address this limitation, Bedford & Cooke (2002) introduced the Vine Copula method, which utilizes a hierarchical tree structure to model high-dimensional dependencies more effectively. Unlike traditional bivariate Copula models, Vine Copulas decompose complex dependency structures into a sequence of pair-copula constructions (PCCs), allowing for greater flexibility in capturing intricate relationships, including tail dependencies and conditional dependencies. This advancement has significantly improved the modeling of high-dimensional financial and economic systems, making Vine Copula a powerful tool in modern risk analysis and multivariate dependence modeling.

The Vine Copula is a flexible multivariate dependence modeling approach that decomposes a high-dimensional joint distribution into a product of multiple lower-dimensional copula functions (Czado,2009). This hierarchical structure, composed of bivariate copulas, effectively captures the complex dependency relationships among variables. Unlike fixed-structure models, the Vine Copula allows dynamic selection of different copula functions (Gaussian Copula, t-Copula, Clayton Copula) to model dependencies across dimensions.

Vine-Copula is a graphical structure used to build the dependency structure between multivariate distributions. It takes the form of a tree structure, where each node represents a bivariate copula, and the entire structure forms a tree.

A Vine structure with d dimensional variables is composed of $d-1$ tree$(T_1, T_2, \ldots, T_d)$ and every tree is composed of many nodes and edges for which the relationships below are satisfied:

(1) For $T_i(i = 1,2, \ldots, d-1)$, there are $d-i$ edges in Ei, with $d-i+1$ nodes in Ni;

(2) Two nodes in tree $i+1$ are only connected by an edge if these nodes share a common node in tree i. The probability density function (PDF) of a Vine Copula-based joint distribution is expressed as:

$$f(u) = \prod_{i=1}^{d} f(u_i) \prod_{k=1}^{d-1} . \prod_{j=1}^{d-k} c_{j;j+k}\left(u_j \middle| u_{j+1:j+k-1}, u_{j+k}\right), \tag{2.23}$$

where $u = (u_1, u_2, \ldots, u_d)$ represents the marginal uniform variables, $f(u_i)$ is the marginal probability density of the i-th variable, $c_{j,j+k}$ is the bivariate copula density function capturing the dependence between variables u_j and u_{j+k}, conditional on intermediate variables(Czado, 2019).

This unrestricted Vine Copula is also referred to as “R-vine Copula” (Regular Vine Copula). The R-Vine Copula is the most generalized form of the Vine Copula framework, allowing for arbitrary tree-based dependency structures without being constrained by the fixed hierarchical or sequential configurations. R-Vine provides greater flexibility in modeling dependencies across multiple dimensions. This makes it particularly well-suited for high-dimensional complex systems, such as the interdependence among multiple financial markets in a global financial network. However, due to the absence of predefined structural constraints, parameter estimation and optimization in R-Vine models are computationally more intensive and require advanced techniques for efficient implementation.

There are two special cases: C-Vine Copula (Canonical Vine Copula) and D-Vine Copula (Drawable Vine Copula).

The C-Vine Copula assumes the existence of a central variable that dominates the dependencies among the other variables, highlighting the central variable's dominant role in the entire system (Kurowicka & Cooke,2006).

The joint distribution function for a C-Vine Copula is expressed as:

$$f(u_1, u_2, \dots, u_d) = \prod_{k=1}^{d-1} \cdot \prod_{j=k+1}^{d} c_{k,j;1,\dots,k-1}\left(F(u_k|u_1, \dots, u_{k-1}), F\left(u_j|u_1, \dots, u_{k-1}\right)\right) \prod_{i=1}^{d} f_i(u_i). \quad (2.24)$$

The 5d C-Vine Copula Tree can draw as follow:

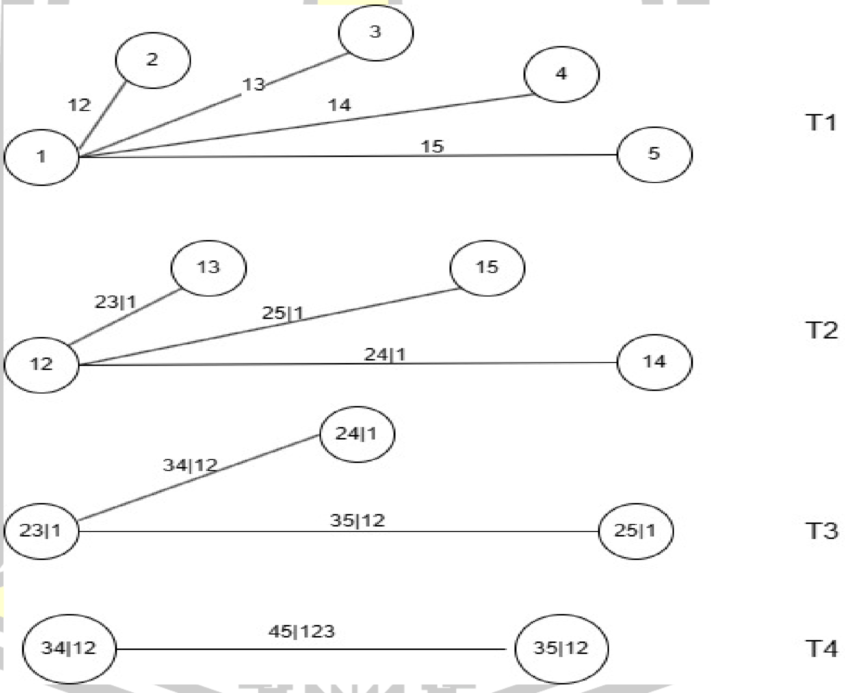


Figure 2: 5d C-Vine Copula Tree

We can see from Figure 2 that C-Vine Copula structure is a hierarchical tree model, characterized by a central node that governs the dependency relationships among all other variables. In each level of the hierarchy, the root node is directly connected to all other variables, forming a star-like dependency structure. The high-dimensional structure is extended through conditional dependencies, where lower-level copulas are conditioned on higher-level copulas. This framework is particularly suitable for modeling dependency structures dominated by a key driving factor, such as financial markets where a benchmark index influences multiple assets or supply chain networks where a central supplier affects multiple downstream firms.

The D-Vine Copula assumes that all variables are treated equally, with no specific core variable dominating the dependence structure. The joint distribution of the variables is constructed using a chain of pair-copula functions, describing the dependency relationships through a chain-like structure (Kurowicka & Cooke,2006). The formula of D-Vine Copula as follow:

$$
\begin{aligned}
&f(u_1,u_2,\dots,u_d)\\
&=\prod_{i=1}^{d} f_i(u_i)\prod_{j=1}^{d-1}\cdot\prod_{i=1}^{d-j} c_{i,i+j;D_{i,j}}\big(F(u_i|D_{i,j}),F(u_{i+j}|D_{i,j})\big),\\
&D_{i,j}=\{u_{i+1},u_{i+2},\dots,u_{i+j-1}\}.
\end{aligned}
\tag{2.25}
$$

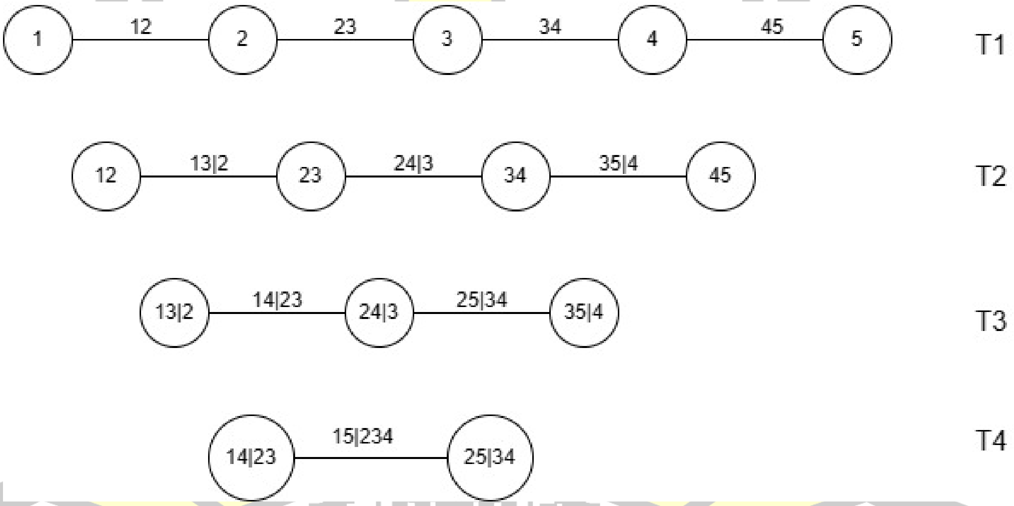


Figure 3: 5d D-Vine Copula Tree

The D-Vine Copula structure follows a sequential (chain-like) dependency structure, where dependencies are established progressively between adjacent variables. Unlike the C-Vine Copula, it lacks a central node; instead, dependencies are formed sequentially based on the ordering of neighboring variables. This structure is particularly well-suited for time series modeling and supply chain analytics, where temporal or sequential dependencies play a crucial role in capturing the dynamic evolution of relationships over time.

Vine Copulas consist of a sequence of nested trees that describe the pair Copula functions unconditionally in the first tree and conditionally for the rest of the trees. Based on Kendall's τ, the strongest dependence relationships between variables are selected(Nelsen2006). Dissmann et al. (2013) introduced an automated algorithm including finding out an optimal R-vine tree structure, the pair-copula families, and the parameter values of each best pair-copula families. The optimal Copula type for fitting the bivariate Copula is chosen based on the Akaike Information Criterion (AIC). Firstly, the strongest dependence relationship between variables is captured, the degree of dependence between two nodes in the first layer tree is measured by the rank correlation coefficient Kendall’s τ , then built layer by layer using the Dissmann algorithm, and the maximum likelihood estimation method is employed to obtain the optimal parameters of the Copula model. And then the pair copula is estimated between the selected variables.

It is generally believed that Vine Copula model can depict multi-variable asymmetric dependence structure better than the traditional single Copula model, and provide a clear path for tail risk propagation. Zhang Yaoting (2002) systematically elaborated the application of Copula theory in financial risk analysis, and its Vine structure significantly improved the shortcomings of traditional methods in multivariate risk measurement. Mendes et al. (2010) deepened the study of multi-dimensional dependency structure through Vine Copula model, providing theoretical support for cross-market and industry relations. Nguyen, H., & Bhatti, M. I. (2021) reviewed the application of Vine Copulas in financial dependence modeling and discussed their latest practices in risk management, portfolio optimization, and asset pricing. Czado, C., & Nagler, T. (2022) focused on recent advancements in Vine Copulas for risk management and dependence structure analysis. Almeida, C., & Czado, C. (2022) analyzed dependence structures in energy markets, with a particular emphasis on the interconnectedness between crude oil, natural gas, and electricity markets. Zhang, Y., & Wang, Y. (2023) proposed a hybrid model combining Vine Copulas with machine learning methods (such as random forests and neural networks) for financial risk prediction. Li, J., & Zhang, Y. (2023) used Vine Copulas to measure systemic risk in Chinese financial markets as a case study and analyzed its transmission pathways.

2.1.2.4 Tail Dependence

Tail dependence is a crucial concept in dependence structure theory, used to describe the co-movement of random variables under extreme conditions. It characterizes the probability that one variable reaches an extreme level given that another variable is also at an extreme level, thereby capturing the correlation between extreme events. A higher tail dependence coefficient indicates stronger interdependence between industries in extreme scenarios, implying that industries may be jointly affected by systemic risk.

Tail dependence can be categorized into upper tail dependence and lower tail dependence, typically modeled using Copula functions (Joe, H.1997). By estimating the parameters of the Copula function, the tail dependence coefficients can be accurately quantified, allowing for precise assessment of the extent of dependence under extreme conditions (Coles, 1999)

The formulas for upper and lower tail dependence coefficients are as follows:

Upper Tail Dependence Coefficient:

$$\begin{aligned}\lambda_U &= \lim_{u \to 1^-} P(U_2 > F_2^{-1}(u) \mid U_1 > F_1^{-1}(u)) \\ &= \lim_{u \to 1^-} \frac{1 - 2u + C(u,u)}{1-u},\end{aligned} \tag{2.26}$$

Lower Tail Dependence Coefficient:

$$\lambda_L = \lim_{u \to 0^+} P(U_2 \leq F_2^{-1}(u) \mid U_1 \leq F_1^{-1}(u)) = \lim_{u \to 0^+} \frac{C(u,u)}{u}, \tag{2.27}$$

where $C(u,u)$ is the Copula function describing the joint distribution. $F_1^{-1}(u)$ and $F_2^{-1}(u)$ are the inverse marginal distribution functions of U_1 and U_2, respectively. u is a probability level approaching the extremes (0 or 1).

If $\lambda_U > 0$ or $\lambda_L > 0$, it indicates the presence of tail dependence between variables, meaning they exhibit strong co-movement under extreme market conditions. Conversely, if the coefficient is zero, it signifies tail independence, implying that the extreme fluctuation of one variable does not affect the other (Durante, F., 2016).

Tail dependence plays a crucial role in extreme risk assessment, as it quantifies the co-movement of stock markets, asset returns, or cryptocurrencies under extreme market conditions. Understanding tail dependence helps evaluate risk transmission pathways and enhances the resilience of supply chains by identifying potential vulnerabilities in interconnected systems. Patton, A. J. (2006) used Copula models to study the asymmetry in tail dependence within exchange rate dependence structures. Chollete, L., Heinen, A., & Valdesogo, A. (2009) proposed a multivariate regime-switching Copula model to analyze the tail dependence structure of international financial returns. Bedoui(2023) combined Vine Copulas with machine learning methods to investigate tail dependence issues in financial risk prediction.

2.1.3 Review of Dependence Structures Research

Globalization has intensified the interconnections among financial markets, amplifying linkages across sectors and regions. Understanding these interdependencies is crucial for financial stability, portfolio optimization, and risk management. Dependence analysis has evolved significantly, transitioning from traditional linear correlation methods to more sophisticated nonlinear approaches that capture asymmetric and tail dependencies. This methodological shift has been driven by the limitations of conventional techniques and the increasing complexity of global financial networks.

2.1.3.1 Linear Dependence Models

Early research on dependence structures primarily relied on linear methods, such as covariance analysis, correlation coefficients, and regression-based models. Markowitz's (1952) portfolio theory introduced variance-covariance matrices to assess asset co-movements, forming the foundation for modern portfolio optimization. Vector Autoregressive (VAR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were later developed to examine cross-market dependencies and volatility spillovers (Dungey et al., 2005). These models have been widely applied to investigate financial contagion, as illustrated by Forbes and Rigobon (2002), who studied market linkages during financial crises, and Diebold and Yilmaz (2009), who quantified risk transmission across integrated economies.

However, traditional linear models assume constant relationships and fail to capture nonlinear, asymmetric, or tail-dependent interactions. For instance, studies by Alexander and Barbosa (2008) and Brunnermeier et al. (2009) demonstrated that financial market linkages strengthen during crises, a phenomenon that linear models struggle to fully describe. Similarly, research on supply chains (Sato et al., 2009) highlighted the cascading effects of economic shocks, revealing limitations in purely linear frameworks.

2.1.3.2 Nonlinear Dependence and Copula Models

To overcome these limitations, researchers have increasingly adopted Copula theory, introduced by Sklar (1959), which allows for the modeling of complex nonlinear dependencies. Unlike traditional correlation measures, Copula functions separate marginal distributions from dependence structures, providing a more flexible approach to modeling co-movements. Nelsen (1999) further formalized the mathematical foundations of Copula models, paving the way for their application in finance and risk management.

Patton (2006) extended Copula models to dynamic settings, allowing for time-varying dependence structures. His work demonstrated that financial assets exhibit asymmetric dependence, particularly during extreme market events. McNeil et al. (2005) and Genest and Favre (2007) highlighted the significance of Copula models in capturing tail dependencies, a critical aspect of risk management. However, despite their advantages, traditional bivariate and multivariate Copulas face challenges in capturing high-dimensional dependencies. Gaussian and t-Copulas, for example, assume symmetry, limiting their ability to model extreme co-movements, while Archimedean Copulas impose uniform dependence structures that may not reflect real-world complexities.

2.1.3.3 Vine Copula Models

To address these challenges, Vine Copula models were introduced as a more flexible approach to high-dimensional dependence structures. Joe (1996) proposed the use of Pair Copula Constructions (PCC), which Bedford and Cooke (2001) later formalized into the Vine Copula framework. Aas et al. (2009) further developed these models, establishing their applicability in finance and economics.

Empirical studies, such as Mendes et al. (2010) and Nikoloulopoulos et al. (2012), have demonstrated the superiority of Vine Copula models in capturing cross-market dependencies. Bekaert et al. (2013) and Alexander (2001) used Copula methods to analyze systemic risks, particularly during periods of extreme market turbulence. These advancements have significantly improved risk spillover analysis, enhancing policymakers' ability to assess financial contagion effects.

2.1.3.4 Tail Dependence and Extreme Risk Transmission

Tail dependence is a key feature of dependence structures, indicating the likelihood of extreme events in one market occurring simultaneously with extreme events in another. The tail dependence coefficient quantifies the intensity of co-movements during extreme conditions, helping to differentiate between such occurrences. This measure is crucial in evaluating systemic risk. McNeil et al. (2005) demonstrated that Copula models are highly effective in capturing tail dependence, which plays a significant role in assessing financial stability and analyzing the resilience of supply chains.

Recent research has extended dependence analysis to regional economic frameworks, such as the Regional Comprehensive Economic Partnership (RCEP), and sustainability initiatives, such as Environmental, Social, and Governance (ESG) policies. Wang and Liu (2020) investigated the moderating role of ESG factors on dependence structures, revealing that sustainability policies influence financial co-movements. Scholtens (2018) emphasized that ESG considerations affect asset correlations, impacting investment strategies and risk assessments. These findings suggest that incorporating policy variables into dependence models enhances their predictive power in modern financial markets.

In summary, the evolution of dependence analysis, from linear correlation models to advanced Vine Copula structures, has significantly improved our ability to understand financial linkages and risk transmission. While traditional linear models remain useful for baseline analysis, their inability to capture nonlinear, asymmetric, and tail-dependent relationships limits their effectiveness in crisis scenarios. The adoption of Copula and Vine Copula models has addressed these limitations, providing deeper insights into market dependencies and systemic risks. Future research should further integrate regional economic factors, sustainability considerations, and machine learning techniques to enhance the predictive capabilities of dependence models. As financial markets continue to evolve, leveraging advanced methodologies will be essential for managing risks and ensuring economic resilience in an increasingly interconnected world.

2.2 Extreme Risk spillover

Risk Spillover refers to the spread of market risk from one financial market to another (Engle et al. ,1990). Risk factors in a market, asset, or economy (such as volatility, liquidity risk, credit risk, etc.) are transmitted through a mechanism to other markets, assets, or economies, resulting in increased risk levels in the latter. The risk impact of a market makes the interdependence between markets significantly increased, resulting in the spread of risk between different markets. This kind of risk spillover effect is usually manifested as the risk fluctuation in one market has an impact on other markets, thus triggering a chain reaction. The transmission mechanism can be realized through various channels, including the interconnection of financial markets, cross-border flows of trade and investment, and information transmission.

For the measurement of financial Risk, VaR (Value at Risk) index is commonly used (J.P. Morgan,1996). VaR represents the maximum loss a portfolio can suffer over a given period of time. It considers correlations between price changes in different assets and measures the risks posed by different risk factors and portfolios of financial assets. However, VaR method has some limitations: it assumes that the relationship between variables remains unchanged in a certain period of time in the future, and the data has normal distribution characteristics, which may not be true in actual market operations, so it cannot effectively evaluate the risk of large price fluctuations under extreme market conditions.

Because the empirical data of the financial market often show the characteristics of sharp peak, heavy tail and aggregation effect, the traditional VaR method is difficult to accurately reflect the extreme risk in the market. Therefore, CoVaR (Conditional Value at Risk) method is widely used in risk assessment in recent years (Adrian, T., & Brunnermeier,2011). These methods combine time-varying dynamic Copula and Vine-Copula models to better describe tail correlations and risk spillovers.

2.2.1 VaR

Value at Risk (VaR) is used to measure the maximum loss that a portfolio of financial assets is likely to suffer over a certain period of time at a given level of confidence. VaR provides a quantitative risk metric to help financial institutions assess and manage market risk.

VaR describes the maximum loss a portfolio can suffer over a period of time at a given confidence level, such as 95% or 99%. Mathematically, VaR can be expressed as:

$$VaR_{\alpha} = -inf\{x \in R: P(L \leq x) \geq \alpha\} \tag{2.28}$$

where, α is the confidence level (0.90 and 0.95 and 0.99), L is the loss (negative return) of the portfolio. $P(L \leq x)$ indicates the probability that the loss does not exceed x.

There are three main methods for VaR calculation. Historical simulation, Monte Carlo simulation and parameter method. However, VaR assumes that the return distribution is normal, which cannot accurately capture the peak and thick tail characteristics in the actual market, and usually needs to be combined with other risk management tools.

2.2.2 CoVaR

CoVaR, introduced by Adrian and Brunnermeier (2008), builds upon the traditional Value at Risk (VaR) framework to assess the risk level of one market or asset in the event of an extreme risk occurrence in another. By incorporating a conditional aspect, CoVaR extends VaR to measure the spillover effects of systemic risks. This approach enables the evaluation of the interdependence between different financial institutions and markets, offering insights into their collective contribution to systemic risk. Through the calculation of CoVaR across various financial entities and markets, it is possible to gauge the transmission of risks and the extent to which individual entities influence the stability of the broader financial system.

CoVaR is an extension of VaR and represents the conditional expected value of the loss above the VaR level. It is the average of all losses that exceed the VaR threshold.

$$pr(X_t^1 \leq CoVaR_{\beta,t}^{1|2} | X_t^2 \leq VaR_{\alpha,t}^2) = \beta, \tag{2.29}$$

specifically, X_t^1 represents the returns of variable 1 at time t, and X_t^2 represents the returns of variable 2 at time t. CoVaR quantifies the risk of variable 1 conditional on variable 2 being under extreme risk at a given significance level β.

This measure introduces the conditional aspect into the traditional VaR framework, making it a powerful tool for evaluating systemic risk and risk spillover effects. By calculating CoVaR across different financial institutions or markets, it becomes possible to assess their interdependencies and contributions to systemic risk. Essentially, CoVaR represents the maximum potential loss for entity B when entity A's losses reach its VaR threshold.

Reboredo and Ugolini (2016) further extended the bivariate CoVaR to a high-dimensional setting, allowing the measurement of the risk faced by a particular sector (or variable 1) when multiple sectors are simultaneously under extreme risk conditions. This generalization enables a more comprehensive evaluation of systemic risk in interconnected financial systems.

$$\Pr(X_t^1 \leq \mathrm{CoVaR}_{\beta,t}^{1|2} | X_t^2 \leq \mathrm{VaR}_{\alpha,t}^2, X_t^3, \dots, X_t^n) = \beta. \tag{2.30}$$

Compared to bivariate CoVaR, high-dimensional CoVaR offers a more comprehensive view of the synergistic relationships across multiple sectors. This is because high-dimensional CoVaR accounts for complex dependencies among multiple markets or institutions, making it more suitable for systemic risk assessment in an increasingly interconnected financial environment.

Both VaR (Value-at-Risk) and CoVaR (Conditional Value-at-Risk) are essential tools for risk assessment, but they have different focuses. While VaR measures the potential loss of an individual institution or portfolio within a given confidence level over a specific time horizon, CoVaR extends this concept by assessing the potential losses in one institution or sector given that another institution or sector is under stress. This allows CoVaR to capture the systemic risks and the risk transmission effects that VaR alone may overlook.

The calculation of CoVaR relies on the risk distribution and the modeling approach chosen. In the event of systemic risk or market stress, CoVaR helps quantify the potential loss of a particular institution or portfolio in response to specific events occurring in the broader market. It is particularly useful for identifying vulnerabilities within a financial system during periods of heightened risk, which VaR alone might fail to highlight due to its focus on isolated risks rather than interdependencies.

There are three primary methods used to estimate CoVaR:

(1) Non-Parametric Methods. These methods utilize historical data, along with techniques like extreme value theory, to estimate CoVaR without relying on predefined assumptions about the data's distribution. This approach can be particularly valuable for capturing the risk of extreme events, a feature often overlooked in VaR analysis.

(2) GARCH Models. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are employed to model conditional volatility and estimate CoVaR in environments characterized by fluctuating volatility. These models are commonly used in financial markets where volatility tends to cluster over time and are useful in estimating both VaR and CoVaR, particularly in volatile market conditions.

(3) Copula-Based Methods. Copula functions are used to model the dependence structure between different financial assets or markets, enabling the estimation of CoVaR. Among these, the Vine Copula model is a notable extension, offering greater flexibility in modeling complex dependencies across multiple assets. This makes it particularly useful for high-dimensional risk analysis, capturing the interdependence and spillover effects that may be missed by simpler VaR models.

CoVaR plays a crucial role in analyzing the risk transmission between various financial institutions or markets. By capturing inter-market interdependence and risk spillover effects, it provides valuable insights into the mechanisms of risk transmission. This helps policymakers and financial institutions better understand systemic risk dynamics, offering a more comprehensive approach to risk management than VaR alone, which typically assesses risks in isolation. Together, VaR and CoVaR provide a more robust framework for understanding and mitigating both individual and systemic financial risks.

2.2.3 Review of Risk Spillover Research

In previous research, VaR (Value at Risk) has often been used to measure financial risks. VaR represents the maximum potential loss of a portfolio over a specified time horizon, considering the correlation between the price changes of different assets. It gauges the risk of a financial asset portfolio resulting from various risk factors. In stable market conditions, the potential risk of an asset portfolio can be estimated (Artzner et al., 1999). Karmakar and Khadotra (2022) measured liquidity risk using VaR through a conditional EVT-copula model.

However, the VaR method assumes that relationships between variables remain constant over time and that the data follows a normal distribution, which makes it less applicable to extreme market conditions with high volatility. In real-world markets, correlations between financial assets are complex and exhibit characteristics such as fat tails and volatility clustering. Given that asset returns often display volatility clustering, non-linear dependence structures are typically modeled using time-varying dynamic Copulas and Vine-Copulas to measure tail dependence and risk spillovers in CoVaR and CoES models. Longin and Solnik (2001) studied the tail dependence among global stock markets and found that market co-movements significantly increase during crises. Jammazi et al. (2005) employed a DCC-GARCH-Copula model to analyze the extreme risk spillover between stock and bond markets using data from developed countries over the past 20 years. Zhong et al. (2009) investigated the risk linkage mechanism in Chinese financial markets and empirically applied Copula and CoVaR models, revealing a bidirectional risk spillover between the bond and foreign exchange markets, which was asymmetric. Righi et al. (2014) employed Copula functions to analyze the spillover effect between the Brazilian stock index and the US dollar exchange rate. Reboredo et al. (2015) studied risk spillovers between emerging stock markets and foreign exchange markets. Using Copula models and CoVaR, they found bidirectional and asymmetric spillover effects between stock prices and exchange rates, with spillover magnitudes varying asymmetrically across different countries. Aloui and Aïssa (2016) applied Vine-Copula models to analyze the dynamic relationship between stock markets and exchange rates, demonstrating significant, symmetric, time-varying risk spillovers. Osguie and Kilvana (2019) used Copula and CoVaR methods to examine risk spillovers between different financial markets in Iran. Dungey and Fratzscher (2019) utilized dynamic methods to analyze extreme risk spillovers in financial markets, exploring the interdependencies and risk transmission paths among different asset classes under extreme market conditions.

Song et al. (2020) used the R-Vine Copula model to analyze risk spillover paths in the financial markets of RCEP countries, revealing that regional integration exacerbated co-movements in tail risks. Kwiatkowski and Serwa (2021) employed Vine-Copula models to depict the non-linear dependence structure between financial markets, revealing systemic risk spillover effects under extreme volatility. Li and Yang (2021) focused on extreme risk spillovers among BRICS countries during the COVID-19 pandemic, particularly the interactions between stock and foreign exchange markets.

García and Salazar (2020) applied the CoVaR method to examine risk spillovers among global financial markets during the COVID-19 crisis, analyzing the cross-border transmission mechanisms of extreme risk. Zhou and Li (2021) applied the CoVaR model to investigate the impact of climate-related risks, such as natural disasters and climate change policies, on financial markets. Liu and Zhang (2022) used CoVaR to analyze cross-sector risk spillovers in China’s financial markets. Peng and He (2022) applied CoVaR to study systemic risk spillovers in China’s stock market, exploring the impact of spillovers on market stability and structure.

Existing literature primarily explores the application of the CoVaR model in analyzing extreme risk spillovers and systemic risk transmission. The studies cover various markets (such as stock markets, bond markets, and commodities), countries (including the US, China, and Europe), and economic events (such as the COVID-19 pandemic, the European debt crisis, and climate-related risks). The research indicates that during periods of extreme volatility, the interdependencies between financial markets increase, exacerbating systemic risk spillovers. CoVaR, as an effective tool, helps in measuring and identifying risk transmission and the potential systemic risks between markets.

2.3 Research Gap

Early research on dependence structures predominantly relied on theoretical models and linear correlation tests, utilizing metrics such as Pearson correlation coefficients to analyze the mutual dependence of return series at the mean level. However, these methods are inherently limited in their ability to capture the nonlinear characteristics frequently observed in real-world financial data. As econometric techniques evolved, methods such as Granger causality tests and cointegration tests emerged, offering more sophisticated tools to describe linear correlations between variables. Despite these advancements, the complex and multifaceted causal relationships inherent in financial markets render these methods inadequate for fully capturing the intricate dynamics of financial systems.

The introduction of GARCH family models marked a significant step forward, as they describe the correlation of residuals in asset returns from both mean and variance perspectives, thereby facilitating the study of volatility spillovers across financial markets. However, GARCH models are limited in their capacity to capture nonlinear dependence structures. Copula models, which link the joint distribution of variables to their marginal distributions, provide a more robust framework for measuring nonlinear and asymmetric dependencies. Nevertheless, traditional multivariate Archimedean Copulas assume a uniform dependence structure between any two variables, which fails to align with the heterogeneous interdependence characteristics observed in real-world markets. To address this limitation, Pair-Copula and Vine-Copula models have been developed, offering a decomposed structure that more effectively captures the interdependencies among multivariate markets.

While existing literature has extensively explored risk spillovers and dependence structures in global stock markets, regional markets, and individual countries, there is a notable lack of research specifically addressing the interdependence of financial markets among Regional Comprehensive Economic Partnership (RCEP) member countries, particularly under extreme market conditions. The dynamic changes in interdependence and risk spillover effects among RCEP markets, especially following the implementation of the RCEP agreement, remain underexplored. Current studies have yet to provide a comprehensive analysis of the financial linkages and risk transmission mechanisms within the RCEP region during periods of extreme market volatility, such as financial crises, geopolitical conflicts, or economic recessions.

Existing research on RCEP financial markets has not sufficiently addressed several critical areas, including the lack of detailed quantitative studies examining risk spillovers among RCEP member countries under extreme market conditions, the effects of policy changes resulting from the RCEP agreement on risk propagation and its dynamic evolution, and the role of the RCEP agreement in enhancing financial market resilience and supply chain stability, particularly in the context of increasing global economic uncertainty. To address these gaps, future research should focus on simulating extreme events, such as the COVID-19 pandemic and regional conflicts, to analyze their impact on financial market dynamics within the RCEP region, while integrating advanced methodologies like Conditional Value at Risk (CoVaR) and extreme value theory (EVT) to provide valuable insights into understanding risk contagion and the transmission paths of systemic risks under extreme scenarios. Additionally, research should investigate the dynamic evolution of risk spillovers and systemic risk transmission within RCEP financial markets, particularly in response to policy changes and external shocks, and explore the implications of RCEP policies on regional financial stability, with a focus on enhancing resilience and mitigating systemic risks. Methodologically, future studies should leverage Vine-Copula models to better capture the complex, nonlinear, and asymmetric dependence structures among RCEP financial markets, employ dynamic CoVaR and EVT to quantify systemic risk spillovers and tail dependencies under extreme market conditions, and utilize network analysis to map and analyze the interconnectedness and risk transmission pathways within RCEP financial systems. The findings from such research would have significant practical implications, including informing better risk management practices for financial institutions and policymakers through an enhanced understanding of risk spillovers and systemic risk transmission, guiding the design of more effective regional economic and financial policies by providing insights into the impact of RCEP policies on financial stability, and enabling stakeholders to develop strategies to enhance the resilience of RCEP financial markets and supply chains by identifying key risk transmission pathways.

Chapter 3

Research Methodology

This chapter outlines the research methodology employed in this study. The aim is to systematically analyze the interdependence and risk spillover effects between the financial markets of RCEP member countries and explore the interdependence and risk spillover mechanisms within China's industrial structure under the ESG context. The methodological framework integrates ARMA-EGARCH-skewed-t model, Vine Copula and CoVaR models to analyze not only the dynamic relationships within financial markets but also the interdependencies in the industrial structure, especially under extreme market conditions.

3.1 Data Sources

(1) Stock Market Index Data. The study will select key stock market indices from RCEP member countries (The Shanghai Composite Index for China, the Nikkei 225 for Japan, etc.), ensuring that the data spans a sufficient time period to reflect pre- and post-RCEP implementation changes.

(2) Industries Index Data. Select ESG benchmark indices and Industry-specific indices (e.g., manufacturing, energy, technology, etc.) to examine the interdependence and risk spillover effects across different sectors within China’s economy.

(3) Time Span. Data spans 2019–2024, covering diverse economic phases, including the 2020 COVID-19 shock and the 2022 RCEP implementation

3.2 Steps of Methodology

3.2.1 Data Processing

(1) Exclude Incomplete Samples. Data mismatched with holidays and non-matching trading hours across different countries due to variations in holidays were excluded to ensure consistency and accuracy in the analysis. This preprocessing step ensures that only synchronized and valid data points are included in the analysis.

(2) Logarithmic Return Transformation. Transformed indices data into return sequences by using the logarithmic return formula: $r_t = lnP_t - lnP_{t-1}$, where P_t is the closing price on day t.

(3) Statistical Tests. To ensure the validity of time series modeling, we conduct stationarity tests to examine whether the return series exhibits unit roots or persistent trends. The following tests are employed: Augmented Dickey-Fuller (ADF) Test, examines whether a time series is stationary by testing the presence of a unit root in the autoregressive process. Jarque-Bera (JB) Test, assesses whether the return series follows a normal distribution by evaluating skewness and kurtosis. Ljung-Box Test, checks for autocorrelation in the residuals up to a specified lag h. Engle's ARCH (LM) Test, assesses the presence of autoregressive conditional heteroskedasticity (ARCH) effects in the time series.

(4) Descriptive Statistics. Before applying econometric models, we compute Mean (μ), Variance (σ^2), Skewness, Kurtosis to determine whether the data exhibits properties such as volatility clustering, asymmetry, and heavy tails, which are common in financial time series.

By performing stationarity tests, descriptive statistics, we ensure that the return series is suitable for further econometric modeling. If the series is found to be non-stationary, transformations such as first differencing or log transformation may be applied. The insights from distribution fitting guide the selection of appropriate copula models in the later stages of the study, ensuring robust modeling of dependence structures and risk spillover effects.

3.2.2 Filtering Data

Time series data often exhibit autocorrelation and heteroscedasticity. When applying copula models, it is essential to preprocess the data to remove temporal dependencies such as autocorrelation and volatility clustering. ARMA models are commonly used to correct for autocorrelation, while GARCH models address autoregressive conditional heteroscedasticity. Financial time series data frequently display skewness, leptokurtosis, and heavy tails. In this study, we employ the ARMA-EGARCH-skewed-t model for data filtering, ensuring that residuals are appropriately processed for copula modeling. The procedure consists of the following steps:

(1) ARMA modeling for autocorrelation correction. Utilize Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine optimal lag orders. Estimate parameters using Maximum Likelihood Estimation

(MLE). Select the best model based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

(2) EGARCH for conditional heteroscedasticity. Fit an EGARCH model to effectively capture asymmetric volatility dynamics. The model parameters were estimated and the significance test was performed.

(3) Skewed t-Distribution for Residuals. Assume the residuals follow a skewed t-distribution, accounting for the asymmetric heavy-tailed nature of financial returns.

The formula of ARMA-EGARCH-skewed t model as follows:

$$
\begin{gathered}
r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j r\epsilon_{t-j} + \epsilon_t, \quad \epsilon_t = z_t \sigma_t, \\
\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2) \\
+ \sum_{j=1}^{q} \alpha_j \left(\frac{|z_{t-j}|}{\sqrt{\upsilon - 2}} - \sqrt{\frac{2}{\pi}} \right) + \sum_{k=1}^{r} \gamma_k z_{t-k}, \\
z_t \sim St(\upsilon, \lambda).
\end{gathered}
\tag{3.1}
$$

Where r_t represent the return at time **t**, **μ** be the mean return, $\phi_i$is the autoregressive (AR) coefficients, and $\theta_j$the moving average (MA) coefficients. The error term is denoted as ϵ_t, conditional volatility as σ_t , and standardized residuals z_t follow a skewed-t distribution St. The parameters **ν** and **λ** control the degrees of freedom and skewness, respectively. ω is the constant term, β_i are the autoregressive coefficients of conditional variance, α_j represent asymmetric effect parameters, γ_k capture the leverage effects.

3.2.3 Marginal Distribution

After applying Eq (3.1) to filter the data, we constructed an ARMA(p, q)-EGARCH(1,1)-skewed-t model to obtain the marginal distribution of the log return series. Consequently, the boundary density of the corresponding variable was derived. To ensure the robustness of the model, we conducted autocorrelation and heteroscedasticity tests on the residual series. The standardized residuals for each return series were then obtained and transformed into a uniform distribution over [0,1] using the cumulative distribution function (CDF). Furthermore, the Kolmogorov-Smirnov (KS) test was applied to the residuals to assess whether they follow the assumed skewed-t distribution. This test helps validate the distributional assumptions of the ARMA-EGARCH-skewed-t model, ensuring its suitability for filtering financial time series and accurately modeling their dependencies.

3.2.4 Dependency Structure Modeling with Vine Copula

Vine Copula is a flexible graphical framework used to model the dependency structure among multivariate distributions. It is constructed as a hierarchical tree structure, where each node represents a bivariate copula, and the edges define the conditional dependencies between variables. This approach decomposes a high-dimensional joint distribution into a series of bivariate copulas, enabling the modeling of complex dependency patterns.

In this study, we employ three types of Vine Copulas: C-Vine (Canonical Vine), D-Vine (Drawable Vine), and R-Vine (Regular Vine). Each type has a distinct structure for organizing dependencies:

(1) The C-Vine structure identifies a central variable that serves as the root of the tree. All other variables are connected to this central variable, forming a star-like dependency structure. This approach is particularly useful when one variable plays a dominant role in influencing the others (see Eq. 2.24 for details).

(2) The D-Vine structure arranges variables in a sequential chain, where dependencies are modeled between adjacent pairs. This sequential arrangement is suitable for capturing ordered dependencies, such as time-series data or variables with a natural ordering (see Eq. 2.25 for details).

The R-Vine structure offers the most flexibility, allowing for arbitrary pairwise dependencies to be modeled. It does not impose any specific hierarchy or ordering, making it ideal for capturing complex and asymmetric dependencies in multivariate datasets (see Eq. 2.23 for details).

For each type of Vine Copula, we select the best-fitting bivariate copulas for each pair of variables using the Akaike Information Criterion (AIC). This ensures that the chosen copulas optimally capture the dependency patterns in the data.

Once the bivariate copulas are selected, the correlation parameters of the Vine Copula model are estimated using the maximum likelihood method. To account for the strength and direction of dependencies, Kendall's τ rank correlation coefficient is used as weights in the estimation process. This non-parametric measure of dependence is robust to outliers and provides a reliable basis for parameter estimation.

By leveraging the strengths of C-Vine, D-Vine, and R-Vine Copulas, this methodology enables a detailed and nuanced analysis of multivariate dependencies, providing valuable insights into the underlying dynamics of complex systems.

3.2.5 Tail Dependence

Tail dependence is a critical measure for assessing the degree of co-movement between variables in the extreme tails of their distributions. It quantifies the likelihood that one variable will experience extreme values (either in the upper or lower tail) given that another variable is already in an extreme state. This measure is particularly relevant in financial markets, where extreme co-movements often occur during periods of market stress, such as financial crises or significant policy changes. In this study, tail dependence analysis serves as an essential tool for evaluating extreme risk spillovers and systemic vulnerabilities.

Compute tail dependence coefficients by using the formulas provided in Eq. (2.26) and Eq. (2.27), we selected pairs of variables before and after significant policy or market events, such as the implementation of trade agreements or financial crises. Compare the changes in λ_U and λ_L to assess the impact of these events on market interdependence and risk spillovers.

3.2.6 Extreme Risk Spillover Analysis

The risk spillover analysis is conducted to quantify and visualize how risks propagate between variables in the system. Utilizing the Vine Copula model estimated in earlier steps, apply the Monte Carlo simulation method to estimate CoVaR, facilitating portfolio construction and the exploration of market risk spillover dynamics. Assess conditional losses and quantify spillover effects. Construct spillover matrices based on CoVaR values to visualize bidirectional relationships and analyze temporal trends, providing insights into how policies influence risk transmission.

The steps below describe the methodology for assessing spillover effects using the previously estimated models:

(1) CoVaR Calculation. Utilizing the estimated R-Vine Copula model, compute the CoVaR for each variable under extreme market conditions.

(2) Spillover Matrix Construction. Construct a spillover matrix where rows and columns represent variables (e.g., markets, industries, or commodities), and each cell value quantifies the magnitude of risk transmission. The matrix captures bidirectional spillover relationships, highlighting which variables are primary sources or recipients of risk.

(3) Visualization of Spillover Paths. Use heatmaps or network graphs to visualize the spillover matrix and identify the strongest risk transmission pathways. Nodes represent variables, and edges represent the strength of risk spillovers, weighted by CoVaR values.

3.3 Simulation Experiments

To replicate the varying dependency structures seen in real-world financial markets, we simulated multivariate data under different distribution assumptions. Specifically, we used the following approaches:

(1) Normal Distribution. This distribution assumes symmetric dependencies with no tail dependence, typically serving as a baseline for comparison.

(2) t-Distribution. This distribution features heavier tails, which allows it to capture extreme events and co-movements often observed in financial markets.

(3) Mixed Distributions. By combining normal and t-distributions, this method simulates heterogeneous dependency structures, representing markets that contain both stable and volatile segments.

We generated multivariate data with dimensions of $d=3$, $d=5$ to represent low and high-dimensional datasets. Ensuring a sample size of over 1,000 observations per dataset to maintain statistical reliability. We also introduced varying levels of correlation ($\tau = 0.2$, $\tau = 0.5$, and $\tau = 0.7$) to simulate weak, moderate, and strong dependencies.

First, we analyze the pairwise joint distributions of the data and compare various copulas, such as Clayton, Gumbel, Frank, Normal, and t Copula, to select the optimal copula. Then, for the full-variable copula connection, we compare the gaussian Copula, t Copula, and Vine Copula to assess the ability of the Vine Copula model in capturing complex dependencies and extreme market behaviors. Subsequently, we use the Monte Carlo simulation method to simulate the calculation of VaR and CoVaR based on the Vine Copula, validating the ability of CoVaR in capturing global systemic risk.

3.4 Empirical Study

In this study, we employ a comprehensive and multidimensional dataset to analyze dependence structures and risk spillover effects, focusing on the interplay between regional market integration and sustainability-driven sectoral dynamics. The dataset comprises two key components: stock index data from RCEP countries and ESG aligned industry index data from China. The RCEP stock indices represent the market performance of 15 Asia-Pacific economies. These indices capture the regional market dynamics and interdependencies within one of the world's largest and most economically significant trading blocs, offering a robust foundation for studying financial integration and risk transmission across borders. Complementing this, the ESG-based industry indices from China provide a sector-specific perspective, reflecting the performance of key industries. This dual dataset enables a holistic analysis of how regional and sectoral factors interact, particularly in the context of evolving ESG frameworks and their influence on market behavior.

By applying Vine Copula model and risk spillover analysis, we examine the complex dependencies and risk propagation mechanisms between RCEP markets and Chinese industries. The Vine Copula model allows us to decompose high-dimensional dependencies into pairwise relationships, identifying key drivers of co-movements and tail dependencies. Meanwhile, risk spillover analysis, facilitated by CoVaR and spillover matrices, quantifies the extent to which risks in one market or sector spill over to others, particularly during periods of significant policy changes. We also conduct temporal and event-based analyses to assess how major events—such as the implementation of RCEP, or shifts in ESG-related regulations—impact market interdependencies and risk transmission patterns.

3.5 Flow Chart

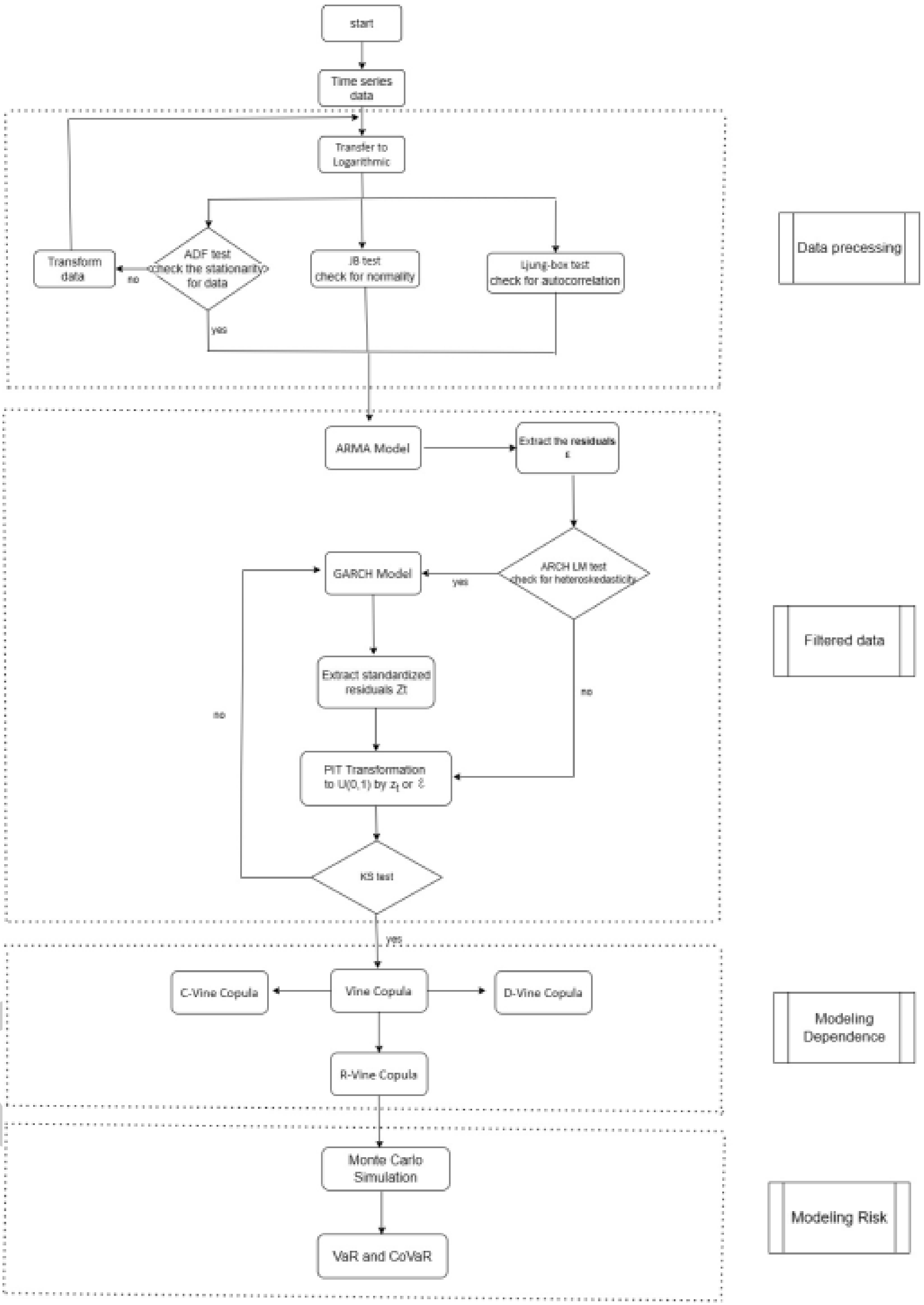


Figure 4: The Flow Chart

Chapter 4
Results

In this chapter, we address two primary research objectives: the analysis of dependence structures and the evaluation of risk spillover effects. The study is carried out in two sequential phases. First, we conduct simulation experiments to model and analyze the theoretical underpinnings of dependence and risk transmission mechanisms. Second, we validate these findings using empirical datasets, including stock index data from RCEP countries and ESG aligned industry index data from China. This two-step approach ensures a robust examination of both theoretical and real-world dynamics. The results are systematically presented, offering insights into the dependence structures and risk spillover patterns observed in regional and sectoral markets.

4.1 Dependence Structure Results

4.1.1 Simulation Results

To validate the stability and flexibility of the Vine Copula model in capturing nonlinear dependence structures, a series of simulation experiments were conducted. Specifically, three-dimensional and five-dimensional datasets were generated, following normal distribution, t-distribution, and a mixed distribution. Different levels of Kendall's τ (0.2, 0.5, and 0.7), representing weak, moderate, and strong dependence, were used. After transforming the data into pseudo-observations, various copula models—including Clayton, Gumbel, Frank, Gaussian (Normal), t copula, and Joe copula—were fitted. Model performance was evaluated based on goodness-of-fit tests and information criteria.

Several key statistics were reported in the result tables. The CvM statistic refers to the Cramér–von Mises criterion, which measures the discrepancy between the empirical copula and the fitted copula. This statistic was chosen because it provides a stable and comprehensive measure of overall model fit, especially in high-dimensional settings. It is particularly well-suited for evaluating complex dependence structures such as those in Vine Copula models.

The parameter θ denotes the estimated dependence parameter for each copula model, reflecting the strength and type of dependence between variables. However, unlike Archimedean copulas, the t-copula does not rely on a single dependence parameter. Instead, it is characterized by a correlation matrix and a degrees-of-freedom parameter, which jointly determine the strength of dependence and the heaviness of the tail dependence. As a result, the θ column in the table does not report a single parameter for the t-copula, since its dependence structure cannot be adequately described by a scalar parameter. The p-value represents the significance level of the goodness-of-fit test; a higher value indicates better model fit to the data.

In copula model selection, the Cross-Validation Score (XV) is a metric used to compare different copula structures (Gaussian, t, Clayton, Gumbel) in terms of their fitting performance, helping to identify the optimal copula structure (Stone, M. 1974). It is based on K Fold Cross-Validation, where the dataset is split into K equal subsets. In each iteration, $K-1$ subsets are used to train the copula model, while the remaining subset serves as the test set. The log-likelihood of the copula model is computed on the test data, and this process is repeated for all K folds. The formula is as follows:

$$\mathrm{XV} = \frac{1}{K}\sum_{k-1}^{K} logL_k, \tag{4.1}$$

where L_k represents the log-likelihood of the test set in the k-th iteration.

The XV value is the average log-likelihood across all folds, serving as a measure of model performance. The copula with the highest XV value is considered the best-fitting model, as it demonstrates superior predictive capability on unseen data.

The optimal copula for each pair of variables was selected based on XV values, while the global dependence structure was modeled using three different approaches: normal Copula, t-Copula, and Vine Copula. Model performance was evaluated using the Akaike Information Criterion (AIC) and log-likelihood values to compare the goodness of fit and tail dependence estimation accuracy.

The results indicate that Vine Copula outperforms both the Gaussian Copula and t-Copula in terms of model selection criteria and tail dependence estimation precision. Specifically, Vine Copula demonstrates exceptional flexibility in capturing complex nonlinear and asymmetric dependencies, making it particularly effective in high-dimensional settings (e.g., five-dimensional datasets). Unlike traditional copulas, which impose rigid structural assumptions, Vine Copula allows for greater adaptability by decomposing high-dimensional dependence structures into pairwise components, thus enhancing its ability to model intricate variable relationships.

4.1.1.1 Samples Following a Normal Distribution

Assuming that the data follows a normal distribution, we generate two sets of data in three and five dimensions for comparison, and Kendall's τ are selected in the range of (0,1), set τ = 0.2, 0.5 and 0.7, n=1000 respectively.

The specific steps are as follows:

Step 1: Set the parameters: mean = 0, variance = 1.

Step 2: Generation 1,000 samples follow normal distribution.

Step 3: Calculate the copula parameters under different τ values and select the optimal copula.

When the dimension is 3, we can see the optimal Copula selection as follow:

Table 2: Define d=3, Data Follows the Optimal Copula Selection of Normal Distribution

Tau	Copula	CvM	θ	p-value	XV
0.2	Clayton	0.1368	0.1665	0.0005	24.9791
	Gumbel	0.0857	1.0979	0.0015	27.4451
	Frank	0.0403	0.9308	0.0794	34.6653
	Normal	0.0261	0.1671	**0.5050**	**37.3207**
	t Copula	0.0522	-	0.0015	35.8083
0.5	Clayton	0.6654	0.6430	0.0005	254.0900
	Gumbel	0.2846	1.4133	0.0005	278.1111
	Frank	0.0829	3.1245	0.0005	298.7256
	Normal	0.0182	0.5034	**0.9296**	**345.7211**
	t Copula	0.1263	-	0.0005	342.5564
0.7	Clayton	1.2703	1.1552	0.0005	565.6261
	Gumbel	0.3158	1.8114	0.0005	679.2597
	Frank	0.1452	5.3788	0.0005	686.4408
	Normal	0.0318	0.7019	**0.2103**	**764.5304**
	t Copula	0.0945	-	0.0005	760.0224

Table 2 demonstrates that when three-dimensional (3D) data follow a normal distribution, the Normal copula emerges as the optimal choice for modeling the dependence structure. This conclusion is supported by the consistently higher p-values and superior statistical performance of the Normal copula across different levels of Kendall's τ (0.2, 0.5, and 0.7).

Table 3: Optimal Copula of 3d Data Following Normal Distribution with Different τ

	Tau=0.2		Tau=0.5		Tau=0.7	
Copula	AIC	LogLik	AIC	LogLik	AIC	LogLik
Gaussian	-109.183	57.592	-687.019	346.510	-1524.620	765.310
t-Copula	-99.649	55.825	-675.049	343.524	-1514.369	763.185
Vine Copula	**-111.816**	**58.908**	**-687.019**	**346.510**	**-1526.311**	**767.156**

Compare with Gaussian Copula, t Copula and Vine Copula, Table 3 clearly indicates that the Vine Copula is the optimal choice for modeling 3D data following a normal distribution, as it consistently achieves the best performance across all tested τ values. While the Gaussian Copula shows competitive results at τ = 0.5, the Vine Copula's flexibility and ability to capture complex dependence structures make it the preferred model overall.

When the dimension increases to 5, we can see the optimal Copula selection as follow.

Table 4: Define d=5, the Optimal Copula Selection for Normal Distribution

Tau	Copula	CvM	θ	p-value	XV
0.2	Clayton	0.2236	0.1966	0.0005	110.8022
	Gumbel	0.1974	1.1167	0.0015	91.5014
	Frank	0.1576	0.9562	0.0005	109.8681
	Normal	0.0201	0.2000	**0.8467**	**148.3322**
	t Copula	0.0896	-	0.0005	149.2092
	Joe	0.4133	1.1417	0.0005	54.3299
0.5	Clayton	1.6467	0.5874	0.0005	621.6014
	Gumbel	0.8600	1.3871	0.0005	655.7848
	Frank	0.4554	2.8839	0.0005	683.8374
	Normal	0.0232	0.5013	**0.9086**	**828.5170**
	t Copula	0.3210	-	0.0005	823.3080
	Joe	2.0622	1.5095	0.0005	481.0443
0.7	Clayton	3.4416	1.0608	0.0005	1310.2400
	Gumbel	1.2832	1.7386	0.0005	1462.4120
	Frank	0.5991	4.9100	0.0005	1481.8610
	Normal	0.0272	0.7012	**0.6758**	**1731.3200**
	t Copula	0.3399	-	0.0005	1718.9310
	Joe	3.6574	1.9776	0.0005	1128.6340

From Table 4, we observe the optimal Copula selection for five-dimensional (5D) data following a normal distribution under different levels of Kendall’s τ (0.2, 0.5, and 0.7). The results indicate that the Normal Copula consistently outperforms other

Copula models, making it the best choice for modeling the dependence structure in 5D normal distribution data.

Table 5: Optimal Copula of 5d Data Following Normal Distribution with Different τ

	Tau=0.2		Tau=0.5		Tau=0.7	
Copula	AIC	LogLik	AIC	LogLik	AIC	LogLik
Gaussian	-294.933	157.467	-1651.771	835.886	-3452.221	1736.111
t-Copula	-264.369	152.185	-1623.580	831.790	-3423.153	1731.576
Vine Copula	**-307.629**	**164.814**	**-1650.544**	**836.272**	**-3453.535**	**1737.768**

Table 5 demonstrates that the Vine Copula is the optimal choice for modeling five-dimensional data following a normal distribution.

4.1.1.2 Samples Following t-Distribution

Assuming that the sample data follows a t-distribution, the specific steps are as follows:

Step 1: Set the parameter: degrees of freedom for 5.

Step 2: Generate 1,000 samples follow t-distribution.

Step 3: Calculate the copula parameters under different τ values and select the optimal copula.

When the dimension is 3d, we can see the optimal Copula selection as follow:

Table 6: Define d=3, the Optimal Copula Selection for t Distribution

Tau	Copula	CvM	θ	p-value	XV
0.2	Clayton	0.1638	0.2910	0.0005	67.9371
	Gumbel	0.0614	1.1671	0.0255	76.7640
	Frank	0.0645	1.3403	0.0045	63.9239
	Normal	0.0490	0.2291	**0.0505**	69.3757
	t Copula	0.0169	-	**0.9605**	**137.6817**
0.5	Clayton	0.6150	0.8129	0.0005	331.2892
	Gumbel	0.1538	1.4983	0.0005	370.2438
	Frank	0.1356	3.4421	0.0005	340.0587
	Normal	0.0527	0.5258	**0.0554**	381.9768
	t Copula	0.0262	-	**0.4780**	**462.5451**
0.7	Clayton	1.1044	1.4202	0.0005	678.0691
	Gumbel	0.2233	1.9342	0.0005	782.0708
	Frank	0.1922	5.6958	0.0005	735.7865
	Normal	0.0391	0.7179	**0.1224**	814.1482
	t Copula	0.0214	-	**0.6139**	**894.6087**

Table 6 demonstrates that when the data follow a t-distribution, the t Copula is the optimal choice for modeling the dependence structure, particularly due to its ability to capture tail dependence and its consistently high p-values across all levels of Kendall's τ. The Normal Copula also performs reasonably well, especially at lower τ values, but it is outperformed by the t Copula in scenarios involving higher dependence and tail behavior.

Table 7: Optimal Copula of 3d Data Following t Distribution with Different τ

	Tau=0.2		Tau=0.5		Tau=0.7	
Copula	AIC	LogLik	AIC	LogLik	AIC	LogLik
Gaussian	-137.407	71.704	-757.865	381.932	-1618.486	812.243
t-Copula	-277.066	144.533	-922.234	467.117	-1791.258	901.629
Vine Copula	**-277.066**	**144.533**	**-923.072**	**467.536**	**-1793.601**	**902.800**

Table 7 demonstrates that the Vine Copula is the optimal choice for modeling three-dimensional data following a t-distribution.

When the dimension increases to 5d, we can see the optimal Copula selection as follow.

Table 8: Define d=5, the Optimal Copula Selection for t Distribution

Tau	Copula	CvM	θ	p-value	XV
0.2	Clayton	0.2130	0.2198	0.0005	125.405
	Gumbel	0.2063	1.118	0.0015	101.4041
	Frank	0.1857	0.9486	0.0005	100.18
	Normal	0.0388	0.1933	**0.0644**	138.0357
	t Copula	0.0216	-	**0.536**	**301.3657**
	Joe	0.4752	1.1309	0.0005	62.57483
0.5	Clayton	1.5067	0.6434	0.0005	647.3044
	Gumbel	0.8048	1.3983	0.0005	665.4633
	Frank	0.4727	2.9168	0.0005	651.5407
	Normal	0.0557	0.4867	**0.0684**	780.5367
	t Copula	0.0316	-	**0.3581**	**983.5103**
	Joe	2.0832	1.5148	0.0005	489.7291
0.7	Clayton	3.4416	1.0608	0.0005	1310.2400
	Gumbel	1.2832	1.7386	0.0005	1462.4120
	Frank	0.5991	4.9100	0.0005	1481.8610
	Normal	0.0272	0.7012	**0.6758**	**1731.3200**
	t Copula	0.3399	-	0.0005	1718.9310
	Joe	3.6574	1.9776	0.0005	1128.6340

Table 8 demonstrates that the optimal Copula for modeling 5D t-distributed data depends on the level of dependence (τ). For low to moderate dependence (τ = 0.2 and τ = 0.5), both the Normal Copula and t-Copula can be considered optimal, with the t-Copula having a slight edge due to its higher p-values. For high dependence (τ = 0.7), the Normal Copula is the optimal choice, as it achieves the highest p-value and provides the best fit to the data.

Table 9: Optimal Copula of 5d Data Following t Distribution with Different τ

	Tau=0.2		Tau=0.5		Tau=0.7	
Copula	AIC	LogLik	AIC	LogLik	AIC	LogLik
Gaussian	-294.88	157.441	-1577.2	798.578	-3452.221	1736.11
t-Copula	-595.03	317.515	-1947.2	993.59	-3423.153	1731.58
Vine Copula	**-590.15**	**315.073**	**-1953.7**	**996.858**	**-3453.535**	**1737.77**

Table 9 clearly demonstrates that the Vine Copula is the optimal choice for modeling five-dimensional data following a t-distribution.

4.1.1.3 Samples with Mixed Distributions

Assuming that each variable in the sample follows a mixed distribution, the specific steps are as follows:

Step 1: Parameter Setting

The first variable follows a normal distribution (mean = 0, variance = 1).

The second variable follows a t-distribution (degrees of freedom = 5).

The third variable follows an exponential distribution ($\lambda = 1$).

Step 2: Generate 1000 samples with the specified distributions.

Step 3: Calculate the copula parameters under different tau values and select the optimal copula.

Table 10: Define d=3, the Optimal Copula Selection for Mixed Distribution

Tau	Copula	CvM	θ	p-value	XV
0.2	Clayton	0.088	0.188	0.0005	34.091
	Gumbel	0.105	1.091	0.0005	20.848
	Frank	0.040	0.908	0.1014	33.031
	Normal	0.019	0.170	**0.9246**	**37.802**
	t Copula	0.052	-	0.0025	37.916
0.5	Clayton	0.713	0.640	0.0005	254.694
	Gumbel	0.227	1.417	0.0005	284.379
	Frank	0.069	3.133	0.0025	305.026
	Normal	0.018	0.499	**0.9096**	**336.455**
	t Copula	0.099	-	0.0005	337.713
0.7	Clayton	1.487	1.147	0.0005	563.761
	Gumbel	0.331	1.803	0.0005	662.189
	Frank	0.103	5.315	0.0005	681.717
	Normal	0.017	0.698	**0.9206**	**752.696**
	t Copula	0.114	-	0.0005	752.832

Table 10 shows that the Normal Copula consistently passes the goodness-of-fit test across all τ levels (p-values > 0.9), with low test statistics and high XV scores. It provides the most stable and accurate fit, making it the optimal choice for modeling dependence in mixed-distribution data.

Table 11: Optimal Copula of 3d Data Following Mixed Distribution with Different τ

	Tau=0.2		Tau=0.5		Tau=0.7	
Copula	AIC	LogLik	AIC	LogLik	AIC	LogLik
Gaussian	-105.440	55.720	-657.743	331.871	-657.743	331.871
t-Copula	-95.675	53.837	-650.771	331.385	-650.771	331.385
Vine Copula	**-110.528**	**58.264**	**-657.742**	**331.871**	**-657.742**	**331.871**

Table 11 clearly demonstrates that the Vine Copula is the optimal choice for modeling three-dimensional data following a mixed distribution.

When the dimension increased to five, we can see the optimal Copula selection as follow.

Table 12: Define d=5, the Optimal Copula Selection for Mixed Distribution

Tau	Copula	CvM	θ	p-value	XV
0.2	Clayton	3.1704	1.1278	0.0005	1394.121
	Gumbel	1.0165	1.7796	0.0005	1536.985
	Frank	0.50122	5.1106	0.0005	1551.444
	Normal	0.04832	0.71099	**0.08442**	**1782.728**
	t Copula	0.2591	-	0.0005	1782.554
	Joe	3.2661	2.0294	0.0005	1200.715
0.5	Clayton	3.1591	1.1719	0.0005	1432.879
	Gumbel	1.4151	1.7963	0.0005	1557.238
	Frank	0.52634	5.2606	0.0005	1600.984
	Normal	0.03557	0.71787	**0.3521**	**1829.917**
	t Copula	0.33072	-	0.0005	1825.431
	Joe	4.1337	2.0401	0.0005	1189.874
0.7	Clayton	3.4416	1.0608	0.0005	1335.33
	Gumbel	1.2832	1.7386	0.0005	1463.313
	Frank	0.5991	4.9100	0.0005	1481.8610
	Normal	0.0272	0.7012	**0.6758**	**1731.3200**
	t Copula	0.3399	-	0.0005	1718.9310
	Joe	3.6574	1.9776	0.0005	1128.6340

Table 12 demonstrates that the Normal Copula is the optimal choice for modeling five-dimensional data following a mixed distribution.

Table 13: Optimal Copula of 5d Data Following Mixed Distribution with Different τ

	Tau=0.2		Tau=0.5		Tau=0.7	
Copula	AIC	LogLik	AIC	LogLik	AIC	LogLik
Gaussian	-3573.5	1796.74	-3662.8	1841.4	-3452.221	1736.11
t-Copula	-3541.1	1790.54	-3636.5	1838.27	-3423.153	1731.58
Vine Copula	**-3574.9**	**1797.47**	**-3668.2**	**1845.1**	**-3453.535**	**1737.77**

Table 13 demonstrates that the Vine Copula is the optimal choice for modeling five-dimensional data following a mixed distribution.

4.1.1.4 Analysis of Simulation Results

From the simulation results, it is evident that the Normal Copula performs poorly in datasets with heavy tails and asymmetric dependencies. Its inability to capture extreme co-movements and tail dependence makes it unsuitable for datasets with significant tail risks. The t-Copula improves upon the Normal Copula by incorporating tail dependence, making it more effective for modeling heavy-tailed data. However, it still falls short in capturing asymmetric dependencies and complex high-dimensional structures, limiting its applicability in more intricate scenarios.

Vine Copula consistently outperforms both the Normal Copula and t-Copula across all metrics, including AIC, log-likelihood, and tail dependence accuracy. Its hierarchical structure allows it to decompose high-dimensional dependencies into a series of bivariate Copulas, enabling it to accurately model complex dependency patterns. This flexibility makes the Vine Copula highly adaptable to data of different dimensions, distributions, and correlation coefficients. Particularly in high-dimensional datasets with complex dependency structures, the Vine Copula demonstrates unique advantages, as it can capture both linear and nonlinear dependencies with precision.

The Vine Copula's ability to model diverse distribution characteristics and complex dependencies makes it a powerful tool for empirical data analysis. By leveraging this model, researchers and practitioners can gain deeper insights into market dynamics, including risk spillovers, systemic vulnerabilities, and extreme co-movements. This provides a more accurate analytical framework for risk management, portfolio optimization, and financial decision-making, highlighting the Vine Copula's practical significance in both academic research and real-world applications.

4.1.2 Application Results of RCEP Countries' Dependence Structure

In this section, we select multiple countries within the framework of the Regional Comprehensive Economic Partnership (RCEP) as research subjects to conduct a comprehensive analysis of the dependence structures between these countries from a horizontal perspective. By constructing a Vine Copula model, we focus on examining the interdependence of financial markets across RCEP member countries and exploring how market turbulence in one country or region impacts the financial stability of other member states. This analysis not only enhances our understanding of the economic linkages within the RCEP framework but also provides valuable insights for policymakers to better anticipate, prevent, and respond to regional economic risks. The findings will contribute to strengthening regional financial cooperation and promoting sustainable economic development among RCEP members.

4.1.2.1 Population and Sample

We selected the stock market indices of member countries within the RCEP that can represent the overall performance of the stock market. Considering data availability, Brunei, Laos, Myanmar, and Cambodia have relatively lower total foreign trade volumes and weaker financial market development compared to other countries. Therefore, this study focuses on 11 countries for analysis, including China, Thailand, Singapore, Malaysia, Japan, South Korea, New Zealand, Australia, the Philippines, Indonesia, and Vietnam, to study the dependent structure of these countries' stock markets before and after the implementation of the RECP. We can get the stock index data from website https://cn.investing.com/.

We collected daily trading index data for each country spanning from January 1, 2019, to November 21, 2023. The dataset included index of China (CSI 1000), Thailand (SET), Singapore (STI), Malaysia (KLSE), Japan (TOPX1000), Korea (KOSPI50), New Zealand (NZMC), Australia (ASX200), Philippines (PSI), Indonesia (JCI), and Vietnam (VN30).

After excluding data mismatched with holidays and non-matching trading hours across different countries due to variations in holidays and market operating hours, a total of 1,184 sample sets were obtained. To investigate the impact of RCEP, the whole sample is divided into two sub-samples: Sub-sample 1, representing the period before the implementation of the RCEP framework (from January 1, 2019, to January 1, 2022), with a sample size of 735; Sub-sample 2, covering the period from the implementation of the RCEP framework until the present (from January 1, 2022, to November 21, 2023), with a sample size of 524. The stock market indices for various countries are transformed into return sequences by using the logarithmic return formula $r(t) = lnP(t) - lnP(t-1)$, Pt is the closed price on day t. This transformation results in logarithmic return sequences.

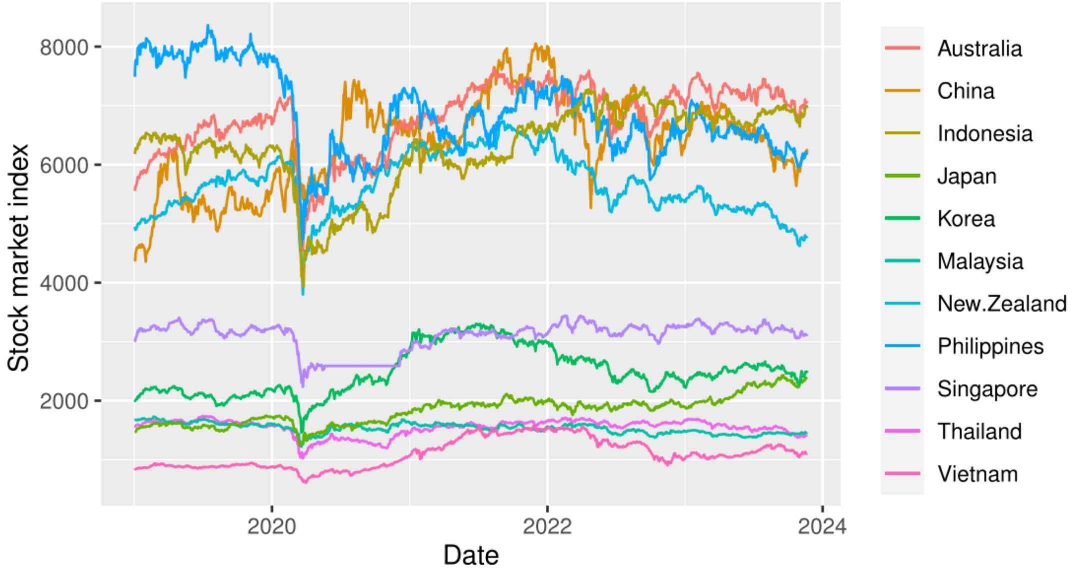


Figure 5: The Index of Stock Markets

From the time series of stock market indices depicted in Figure 5, a clear comparison can be made between the volatility patterns before and after the implementation of the Regional Comprehensive Economic Partnership (RCEP). Prior to RCEP, stock indices across member countries exhibited moderate fluctuations, reflecting relatively stable market conditions. However, the onset of the COVID-19 pandemic at the end of 2019 triggered a sharp decline in stock indices globally, including those of RCEP countries. This period of heightened volatility persisted through 2020 and 2021, as markets grappled with the economic fallout of the pandemic.

Following the implementation of RCEP in 2022, the recovery trajectories of stock indices began to diverge among member countries. For instance, the stock markets of Australia, China, Japan, and Korea showed a relatively stable upward trend, suggesting resilience and a faster recovery pace. In contrast, the indices of New Zealand, the Philippines, Thailand, and Vietnam experienced more pronounced fluctuations and a slower recovery, indicating varying degrees of economic resilience and policy effectiveness. Additionally, in 2023, some countries' stock markets faced renewed turbulence, likely influenced by global economic uncertainties, monetary policy shifts, and regional factors.

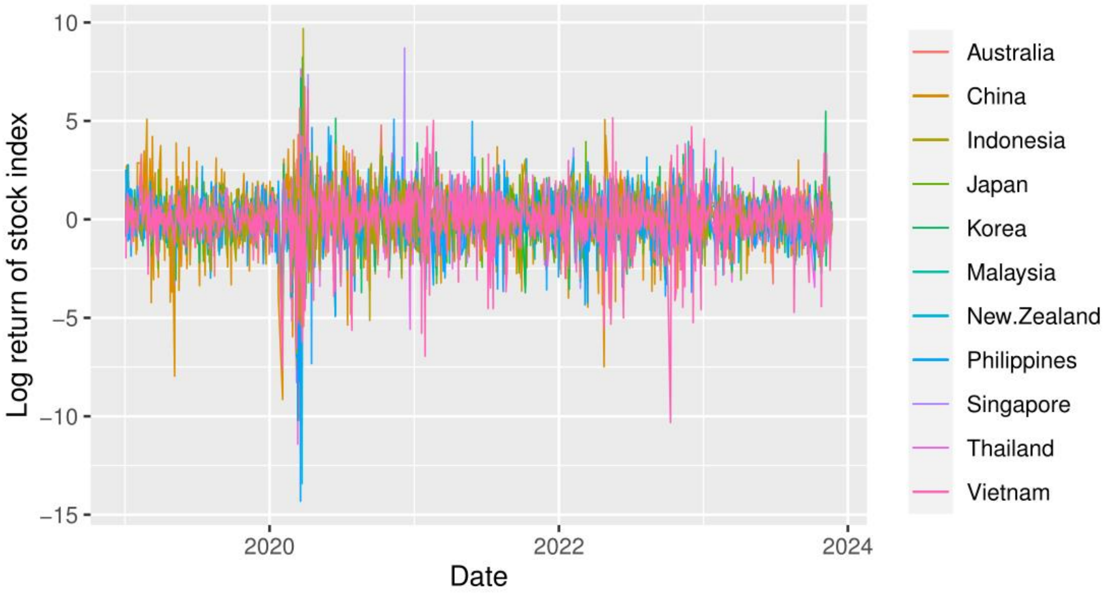


Figure 6:The Log Return of Stock Index

From the log return of stock index show in Figure 6, it is observed that the daily logarithmic return sequences exhibit significant volatility and concentration, displaying clustering of volatility. Extreme values are concentrated within specific time intervals. Descriptive statistics are applied to the return sequences, including mean, standard deviation, skewness, and kurtosis.

Table 14: Summary Statistics of Stock Indices

Countries	Mean(10^4)	SD	Skew	Kurtosis	JB	ADF	Box-Ljung Q	p-value
China	**2.900**	**0.014**	**-0.709**	**6.403**	**670.62*****	**-9.95**	**11.966**	**0.287**
Thailand	-0.805	0.011	-2.004	27.927	31447***	-8.68	51.115	0.000
Malaysia	-1.106	0.008	-0.088	11.969	3970.4***	-10.1	20.700	0.023
Japan	**4.019**	**0.011**	**-0.047**	**6.540**	**618.68*****	**-10.4**	**10.257**	**0.418**
Korea	1.878	0.012	-0.141	10.113	2499.8***	-10.1	26.292	0.003
Singapore	0.158	0.009	0.371	25.171	24277***	-9.18	57.172	0.000
New Zealand	-0.336	0.009	-2.949	49.851	1100***	-9.55	48.963	0.000
Australia	2.042	0.011	-1.198	16.818	9702.7***	-8.42	91.307	0.000
Philippines	-1.584	0.014	-1.517	18.755	12700***	-10.0	19.562	0.034
Indonesia	1.004	0.010	-0.214	15.279	7447.2***	-10.8	21.198	0.020
Vietnam	**2.187**	**0.014**	**-1.123**	**9.491**	**2326.9*****	**-9.57**	**9.667**	**0.470**

From Table 14, it can be observed that, except for Singapore, the return sequences of stock indices for all countries exhibit left-skewness, with kurtosis exceeding 3. This indicates that the log return sequences display sharp peak and left-skewness characteristics. We use ADF (Augmented Dickey-Fuller) test, Jarque-Bera(JB) test, Ljung-Box test to check stationarity and independence of time series data. The JB test is used to judge whether the sample data conforms to the normal distribution. If the value is significantly greater than 0.05, it indicates that the sample data does not follow a normal distribution. ADF test is used to analyze the stationary of logarithmic return series of stock index. The Ljung-Box test can determine whether the sequence is purely random, and avoid auto-correlation affecting the accuracy of the time series model. If the observed values are not mutually independent, then the observations may be correlated with another observation after a certain period of time, the time series data has ARCH effect.

It can be observed that the JB statistic is significantly larger than 0 for all sequences, indicating rejection of the normality assumption. The p-values of the ADF test are significantly rejecting the null hypothesis, suggesting the sequences is stationary. The Ljung-Box Q (10) test is for the ARCH effect with a lag of 10 periods. Except for China, Japan, and Vietnam, the stock market log returns exhibit autocorrelation, and significant ARCH effects are observed. Through the aforementioned data processing steps, the original time series data of stock indices are transformed into stationary return series.

4.1.2.2 Marginal Distribution Analysis

In this study, the ARMA(p, q)-EGARCH(1, 1)-skewed-t model is established to model the marginal distribution of the log return series of RCEP countries, and the boundary density of the corresponding variables is obtained. Autocorrelation and heteroscedasticity tests are conducted on the resulting residual sequences, and the standard residual sequence for each return series is derived.

Table 15: The Estimator of ARMA Model for Each Country

Countries	p	q	AR1	AR2	AR3	AR4	AR5	MA1	MA2	MA3	MA4	MA5
China	1	0	0.032									
Thailand	5	5	-0.747	-0.282	-0.273	-0.732	-0.977	0.751	0.291	0.285	0.744	1
Malaysia	2	5	0.436	-0.973				-0.513	1.067	-0.093	0.046	0.023
Japan	4	4	0.369	-0.34	0.339	0.614		-0.394	0.365	-0.381	-0.61	
Korea	5	3	-0.142	-0.196	-0.923	0.016	0.055	0.151	0.247	0.971		
Singapore	5	4	0.775	0.187	0.457	-0.604	-0.032	-0.789	-0.205	-0.429	0.632	
New Zealand	5	3	0.875	0.47	-0.874	-0.083	0.117	-0.875	-0.382	0.832		
Australia	5	4	0.628	-0.557	-0.392	0.335	-0.031	-0.675	0.584	0.328	-0.293	
Philippines	4	4	0.127	0.502	0.394	-0.813		-0.178	-0.549	-0.394	0.851	
Indonesia	5	5	0.065	-0.349	0.09	0.453	-0.385	-0.146	0.306	-0.069	-0.43	0.503
Vietnam	1	0	0.001									

Table 15 presents the estimators of the ARMA model for each country, including the optimal values of p (autoregressive order) and q (moving average order), as well as the estimated coefficients for the AR (autoregressive) and MA (moving average) components.

Table 16: The Estimator of EGARCH Model for Each Country

Countries	μ	α	β	ω	γ	skew	shape	LLH	AIC
China	-0.065	-0.074	0.928	-0.619	0.226	0.835	6.82	3440.66	-5.798
Thailand	-0.233	-0.092	0.981	-0.182	0.133	0.918	3.977	4069.316	-6.845
Malaysia	-0.274	-0.025	0.99	-0.101	0.119	0.962	4.537	4248.707	-7.153
Japan	0.4	-0.127	0.957	-0.398	0.103	0.936	7.957	3808.871	-6.409
Korea	-0.084	-0.117	0.947	-0.484	0.196	0.889	7.917	3754.309	-6.316
Singapore	0	-0.157	0.961	-0.656	1.469	1	3.208	5128.125	-8.635
New Zealand	0.011	-0.119	0.955	-0.448	0.193	0.968	5.045	4258.387	-7.168
Australia	0.006	-0.131	0.978	-0.205	0.119	0.751	4.991	3998.348	-6.727
Philippines	-0.301	-0.054	0.973	-0.234	0.125	0.932	4.439	3620.78	-6.091
Indonesia	0.066	-0.088	0.981	-0.178	0.137	0.904	4.32	4028.127	-6.776
Vietnam	0.403	-0.054	0.965	-0.301	0.206	0.89	3.694	3615.216	-6.093

Table 16 presents the r estimator from EGARCH model. It can be observed that the β (GARCH effect coefficient) is close to 1, such as Malaysia (0.99), New Zealand (0.955), and Australia (0.978), indicating a high degree of volatility persistence. This suggests that market fluctuations take a long time to dissipate after a shock. The γ (leverage effect coefficient) reflects the asymmetry of the market. If relatively high, implying that negative shocks have a greater impact on volatility, demonstrating a significant leverage effect in these markets. Like Vietnam (0.206), New Zealand (0.193), Korea (0.196), and Indonesia (0.137).

The ω (benchmark volatility level) reflects the level of volatility inherent in the market. China (-0.619), Japan (-0.398), and Korea (-0.484) have lower ω values, indicating that these markets exhibit relatively low baseline volatility.

The skew parameter reflects the symmetry of return distributions, where values close to 1 suggest a more symmetric return distribution.

The kurtosis parameter measures the fat-tailed characteristics of the distribution, with higher values indicating a greater likelihood of extreme returns and higher market risk. The shape values of Japan (7.957), New Zealand (5.045), Malaysia (4.537) and other countries are large, indicating that the occurrence probability of extreme return events in these markets is higher, and the tail risk is more significant.

4.1.2.3 Joint Distribution Analysis

In this section, we employ Gaussian Copula, t Copula, and Vine Copula to fit the stock market data of RCEP countries and evaluate their performance in capturing market dependence structures. The results are summarized in Table 17, which compares the models based on the Akaike Information Criterion (AIC) and Log-Likelihood Value (LLH).

Table 17: The Performance of Copula

Copula	AIC	LLH
Gaussian	-2615.71	1362.854
t-Copula	-2654.3	1437.152
Vine Copula	-2848.31	1494.154

From the results, we observe significant differences in terms of AIC and LLH among the three Copula models. Gaussian Copula has the highest AIC value (-2615.71) and the lowest LLH value (1362.854), indicating that this model performs relatively poorly in capturing the dependence structure of RCEP stock markets. Since the Gaussian Copula can only describe symmetric dependencies and fails to capture tail dependence under extreme market conditions, its applicability in financial market analysis is limited. t Copula outperforms the Gaussian Copula, with a lower AIC value (-2654.30) and a higher LLH value (1437.152). This suggests that the t Copula provides a better fit for the dependence structure of RCEP stock markets, especially in extreme market fluctuations. Due to its tail dependence properties, the t Copula can more accurately capture market co-movements during financial crises. Vine Copula exhibits the lowest AIC value (-2848.31) and the highest LLH value (1494.154), indicating that it is the best-performing model for fitting the dependence structure of RCEP stock markets. By decomposing high-dimensional dependencies into multiple conditionally dependent bivariate Copulas, the Vine Copula allows for greater flexibility in capturing the nonlinear, asymmetric dependencies between different markets and better represents tail risk spillover effects. Compared to the other two models, Vine Copula is superior in describing the dynamic dependence structure and risk transmission pathways in financial markets.

4.1.2.4 Vine Copula Structure

In order to study whether the implementation of RCEP has a significant impact on the interdependence between the capital markets of the countries (regions) in the agreement, this paper takes January 1, 2022 as the segmentation point. The whole sample was divided into two periods before the implementation of RCEP (January 1, 2019 to December 31, 2021) and after the implementation of RCEP (January 1, 2022 to November 21, 2023). With Kendall's tau rank correlation coefficient as the weight, R-vine-Copula models are built for the new sequences in these two time periods using the maximum spanning tree algorithm.

Table 18: The Copula Function before RCEP Implementation

Edge	Copula	Parameter	τ
Korea-Vietnam	Gumbel	1.18, -	0.16
Korea-China	BB7	1.08, 0.25	0.15
Korea-Singapore	BB8	2.44, 0.71	0.22
Malaysia-Philippines	BB1	0.2, 1.22	0.25
Indonesia-Philippines	BB1	0.12, 1.24	0.24
Korea-Thailand	BB1	0.11, 1.25	0.24
Korea-Indonesia	BB1	0.12, 1.24	0.24
Korea-Japan	Gumbel	1.53, -	0.35
Japan-Australia	BB1	0.48, 1.16	0.30
Australia-New Zealand	Gumbel	1.3, -	0.23

The parameter estimation results for the first-layer tree of the R-Vine-Copula function before the implementation of the agreement are presented in Table 18. From the results, it can be observed that there are asymmetrical tail dependence features among the stock markets of different countries. Positive τ values indicate a positive interdependence relationship among the stock markets, with the magnitude of τ indicating the strength of the relationship. The strongest interdependence is observed between the stock markets of South Korea and Japan.

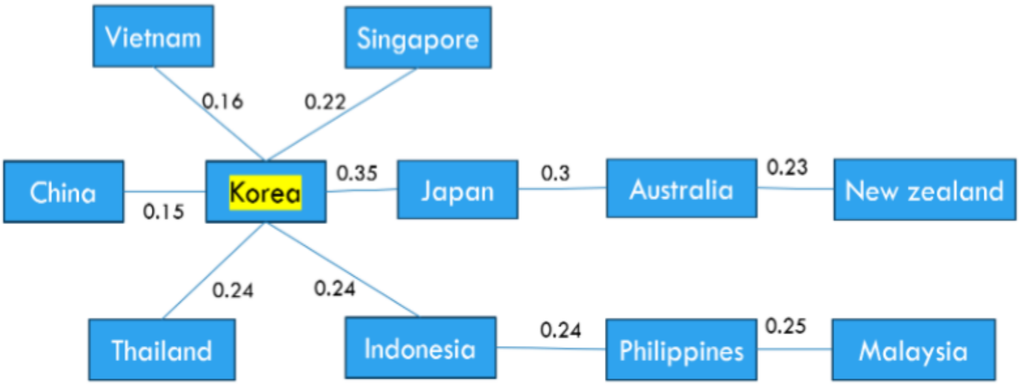


Figure 7:The Vine-Copula Tree1 before RCEP Implementation

Visualizing the interdependence structure of the national stock markets through a tree diagram (as shown in Figure 7), with South Korea as the central node followed by Japan, reveals that these two countries hold significant positions in the financial markets among the RCEP nations. This suggests a central role in the volatility spillover dynamics.

Table 19: The Copula Function after RCEP Implementation

Edge	Copula	Parameter	τ
Thailand-Vietnam	Gaussian	0.28, -	0.18
Korea-China	Frank	1.88, -	0.20
Korea-Indonesia	BB1	0.22, 1.2	0.25
Australia-Philippines	Frank	2.23, -	0.24
Korea-Thailand	Gaussian	0.43, -	0.28
Korea-Malaysia	t	0.4, 5.96	0.26
Korea-Australia	Frank	5.1, -	0.46
Australia-Japan	BB8	4.12, 0.68	0.38
Australia-Singapore	t	0.49, 10.05	0.32
Australia-New Zealand	t	0.41, 12.66	0.27

From Table 19, it can be observed that after the implementation of the RCEP agreement, the τ values have increased, indicating that the implementation of the RCEP agreement has had a certain impact on the economies and finances of each country. It has strengthened the correlation among the stock markets, leading to a closer financial connection. Notably, the correlation between South Korea and Australia is the strongest, reaching 0.46, and the correlation between Japan and Australia has increased from 0.3 to 0.38.

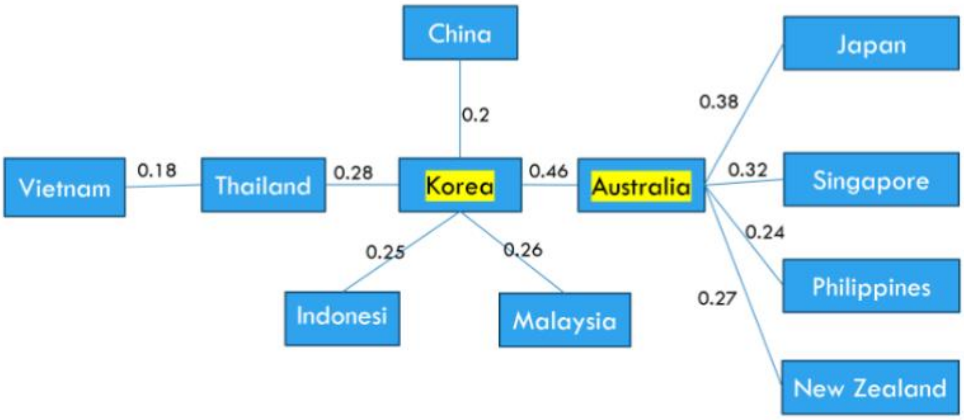


Figure 8:The Vine-Copula Tree1 after RCEP Implementation

Examining the tree diagram in Figure 8, South Korea remains at the central position of volatility spillover, while Japan's influence weakens. Australia's position, on the other hand, strengthens and assumes the second position in the volatility spillover dynamics.

The utilization of the ARMA-EGARCH-t model in this study to analyze marginal distributions of variables present a robust approach. However, it is essential to acknowledge potential limitations arising from the uniform application of this model across all stock index return series. Future research endeavors could address this issue by exploring and comparing various GARCH models. Such an approach would enable the selection of the most appropriate GARCH model for each specific stock index return series, thereby enhancing the accuracy of marginal distribution estimation. Additionally, integrating extreme value theory into the analysis could offer further improvements in estimating marginal distributions, particularly in capturing tail behaviors more effectively.

Furthermore, while the Vine-Copula model effectively captures the overall interdependence structure of stock markets, it is imperative to recognize the dynamic nature of financial markets. These markets are subject to continuous fluctuations, particularly in response to extreme events, which can significantly alter dependence structures. To address this challenge, future research could consider integrating dynamic copula functions into the Vine-Copula model. This approach, as proposed by Claudia Czado (2022), would enable a more accurate depiction of the ever-evolving relationships among financial markets, thereby enhancing the model's predictive power and applicability in real-world scenarios.

4.1.3 Application Results of Chinese Industries' Dependence Structure under the ESG Framework

In this part, we will take the Chinese stock market as the research object and analyze the impact of ESG (environmental, social and corporate governance) policies on the dependency structure between different industries from a deep perspective. We will select the stock indexes of major industries in China's stock market and apply Vine Copula to deeply explore the tail dependence and volatility spillover effect among industries under the background of ESG policy.

Specifically, we will analyze the dependency structure between ESG and different industries, pay attention to the impact of ESG factors on industrial risk spillovers, especially in the case of increasing economic uncertainty, and explore the path relationship of risk spillovers between industries in extreme cases. This analysis not only helps to understand the far-reaching impact of ESG policies on the restructuring of industrial systems, but also provides empirical evidence for investors and regulators to respond more effectively to market risks and promote sustainable development goals.

4.1.3.1 Population and Sample

China Securities ESG benchmark index is selected as the ESG index, and the securities of listed companies with the lowest ESG score of 20% are excluded from the CSI 300 sample, and the remaining securities are selected as the index sample, with 234 remaining samples, to provide performance benchmarks and investment targets for ESG investment. The index of industrial structure is classified according to the first-level industry, and ten industry sector indexes, such as finance, energy, real estate, consumption, manufacturing, transportation, agriculture and forestry, information, medical care and culture, which are greatly affected by ESG policies, are selected respectively. The time span is from January 2, 2019 to July 1, 2024, and a total of 1332 observed values are included. The logarithmic return rate is applied to the industry index, $r(t) = ln(P(t)/P(t-1)) * 100$, and Pt represents the index closing price of the day. The ESG Benchmark Index data were sourced from China Securities Index (https://www.csindex.com.cn), and the industry data were sourced from the Tongdaxin Stock Trading System.

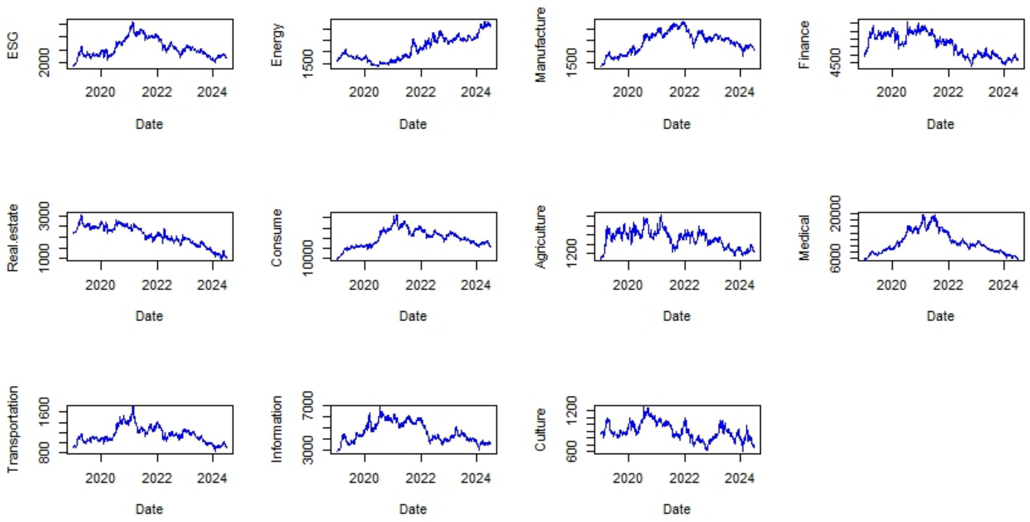


Figure 9: The Index of Each Industry

Figure 9 presents the time series of industry indices from 2019 to 2024, covering ESG index and 10 sectors, such as Energy, Manufacturing, Finance, Real Estate, Consumption, Agriculture, Medical, Transportation, Information, and Culture. Each small panel represents the trend of an industry's index over time. We can observe that Medical, Information, and ESG had strong performance, Energy, Manufacturing, and Agriculture exhibit fluctuating patterns, Real Estate and Finance show a continuous downward trend.

4.1.3.2 Descriptive Statistics

To gain a better understanding of the characteristics of the return data, descriptive statistics were performed. This analysis provides key insights into central tendency, dispersion, and return distribution properties, which help assess overall market behavior. By examining mean, standard deviation, skewness, and kurtosis, we can evaluate the volatility, asymmetry, and presence of extreme values in the return data. Additionally, the Jarque-Bera (JB) test, Augmented Dickey-Fuller (ADF) test, and

Ljung-Box test were performed to examine normality, stationarity, and autocorrelation, respectively, ensuring that the statistical properties of the data align with the requirements for subsequent modeling and analysis.

Table 20: Descriptive Statistics of Sample

Industries	Mean	SD	Skewness	Kurtosis	JB	ADF	Ljung-Box
ESG	0.012	1.214	-0.529	4.408	1145.2***	-11.045***	6.447(0.77)
Energy	0.053	1.618	-0.184	2.295	301.79***	-10.814***	22.77(0.011)
Manufacture	0.033	1.447	-0.503	2.790	490.72***	-10.573***	9.66 (0.47)
Finance	-0.003	1.307	0.333	4.449	1127.7***	-11.42***	10.77(0.37)
Real estate	-0.052	1.786	0.361	2.919	504.24***	-11.354***	15.38(0.118)
Consume	0.037	1.541	-0.157	2.046	239.4***	-11.873***	3.596(0.963)
Agriculture	0.012	1.980	0.153	1.997	228.04***	-11.345***	18.22(0.051)
Medical	0.000	1.805	0.022	1.201	80.983***	-11.055***	17.84(0.058)
Transportation	0.001	1.487	-0.061	2.422	328.43***	-12.165***	13.364(0.20)
Information	0.017	1.813	-0.260	1.808	197.77***	-9.9499***	9.830(0.455)
Culture	-0.017	2.032	-0.199	1.188	87.954***	-11.361***	5.267(0.873)

According to the descriptive statistical analysis in Table 20, the mean return values are negative for the Finance, Real estate, and Culture, while the rest show positive mean returns. Regarding skewness and kurtosis, the data exhibit typical characteristics of leptokurtic and heavy-tailed distributions. The results of the JB test further confirm that all data do not follow a normal distribution. The ADF test rejects the null hypothesis of the presence of a unit root, indicating that the logarithmic returns of all industries are free from unit roots and the series are stationary. The Ljung-Box (LB) test shows that some industry data exhibit certain autocorrelation.

4.1.3.3 Marginal Distribution

Due to the presence of autocorrelation, heteroscedasticity, and leptokurtic features in the return data, the ARMA-EGARCH(1,1)-skewed t model is selected to model each univariate time series. This step is crucial to eliminate time dependency before applying the Vine Copula model. The parameter results are presented in Table 21.

The residual series from the marginal distribution construction have passed the autocorrelation test (LB test) and heteroscedasticity test (ARCH-LM test), with non-significant p-values. This confirms that autocorrelation and heteroscedasticity have been effectively removed, and the residuals are white noise, free from autocorrelation and ARCH effects. These results validate the reasonableness of the established Copula marginal distribution, providing a solid foundation for the subsequent fitting of the Vine Copula model.

Table 21: The Marginal Distribution Fitting Parameter Estimation

Industries	μ	ω	α	β	γ	LLH	LB(1)	LM(7)
ESG	-0.020	0.021	-0.052	0.960	0.224	-2057.790	1.976	1.960
Energy	0.045	0.028	0.039	0.975	0.140	-2430.478	0.407	0.509
Manufacture	0.007	0.041	-0.069	0.945	0.245	-2300.308	3.172	1.635
Finance	-0.001	0.039	0.012	0.941	0.180	-2198.343	0.033	1.051
Real estate	-0.053	0.052	-0.015	0.962	0.187	-2588.963	2.662	3.593
Consume	-0.023	0.030	-0.015	0.971	0.153	-2419.227	2.172	4.739
Agriculture	-0.008	0.036	0.008	0.976	0.141	-2727.786	2.707	6.461
Medical	-0.023	0.032	-0.019	0.973	0.147	-2626.855	2.329	3.202
Transportation	-0.012	0.034	-0.037	0.964	0.155	-2372.457	5.969	2.751
Information	-0.010	0.031	-0.002	0.976	0.145	-2633.965	0.098	4.266
Culture	-0.036	0.037	-0.013	0.975	0.146	-2773.310	3.746	4.878

4.1.3.4 Industry Structure Dependence Analysis Based on Vine-Copula

Based on Copula theory, when variables follow a uniform distribution U(0,1), there exists a copula function C that can construct the joint distribution function from the marginal distributions of the individual variables. To ensure the existence of the copula, the residual sequences of the industry indices, previously calculated, undergo a probability density transformation. The transformed sequences, now following a uniform distribution U(0,1), are used for modeling and analysis.

The Kolmogorov-Smirnov (KS) test is applied to verify whether the transformed sequences follow the uniform distribution on the interval [0,1]. The results show that the KS value for all industry index residuals is 0.00075075, with a p-value close to 1. This indicates that the transformed sequences indeed follow the U(0,1) distribution, validating their suitability for subsequent Vine-Copula modeling. This step ensures the reliability of the copula-based dependence analysis.

This study chooses Vine-Copula structure based on the dependency relationships between the variables to describe the interdependencies between the ESG index and the industrial structure. The C-Vine Copula indicates that all industries are dominated by the ESG variable, with the highest correlation coefficient between the manufacturing industry and ESG.

Table 22: The Copula Function and τ of C-Vine Copula Tree1

Type	Edge	Copula	Para1	Para2	tau
C-Vine Copula	ESG-Agriculture	SG	1.4	0	0.29
	ESG-Transportation	SBB1	0.22	1.75	0.48
	ESG-Medical	t	0.69	12.57	0.49
	ESG-Real Estate	SBB1	0.21	1.51	0.4
	ESG-Energy	SBB1	0.14	1.39	0.33
	ESG-Information	SBB1	0.37	1.65	0.49
	ESG-Consume	t	0.8	24.97	0.59
	ESG-Finance	BB1	0.6	1.78	0.57
	ESG-Manufacture	t	0.85	8	0.65
	ESG-Culture	SBB1	0.12	1.53	0.38

From Table 22, we observe the C-Vine Copula structure for Tree 1, which highlights the dependence between ESG factors and various industries. The table includes different Copula functions—t-Copula, BB1, SBB1, and SG copula. Each capturing unique dependence characteristics. The t-copula has a heavy tail, which means that there is a stronger correlation between the industry and ESG in extreme cases. BB1 copula indicates that variables have different tail dependencies. SBB1 is a hybrid copula suitable for industries with asymmetric dependence characteristics. τ reflects the degree of dependence between ESG and the industry, the greater the τ, the stronger the correlation. From τ value, we can indicate that ESG has the strongest impact on manufacturing, consumption, and financial industries, with Kendall’s τ values of 0.65, 0.59, and 0.57. While agriculture, culture, and real estate are less affected by ESG. From the second tree (Tree 2) in the C-Vine Copula structure, it can be observed that ESG's influence propagates primarily through the manufacturing sector before affecting other industries.

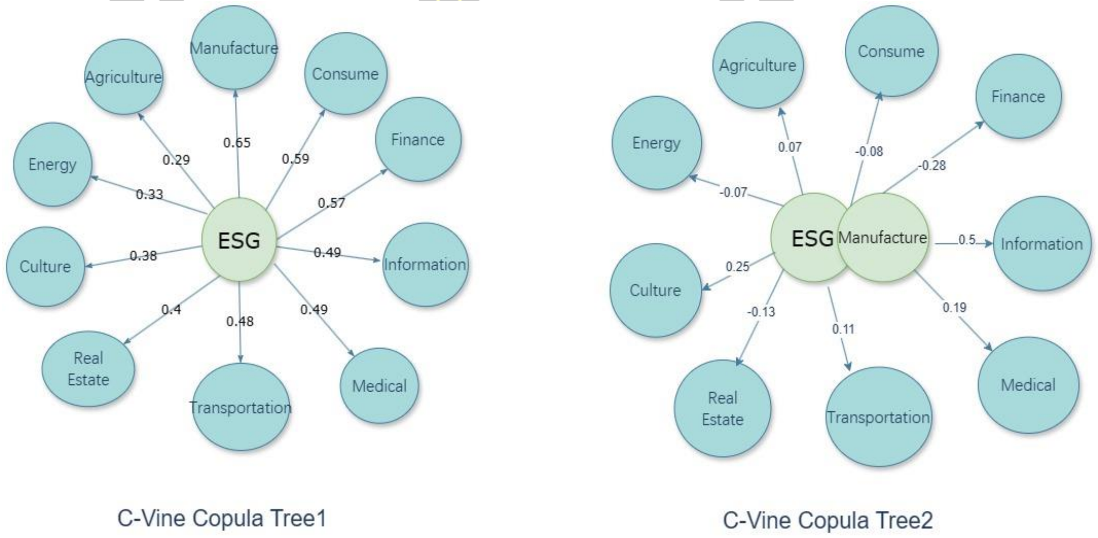


Figure 10: The C-Vine Copula Tree

The C-Vine Copula tree in Figure 10 indicates that ESG serves as the dominant variable influencing all industries, highlighting its critical role in guiding industrial development.

Table 23: The Copula Function and τ of D-Vine Copula Tree1

Type	Edge	Copula	Para1	Para2	tau
D-Vine Copula	Culture-Energy	SG	1.11	0	0.18
	Energy-Real Estate	t	0.41	5.13	0.27
	Real Estate-Finance	SBB1	0.31	1.86	0.53
	Finance-Transportation	SBB1	0.17	1.44	0.36
	Transportation-Medical	t	0.55	9.37	0.37
	Medical-Information	SBB1	0.2	1.48	0.39
	Information-Manufacture	t	0.85	7.24	0.65
	Manufacture-ESG	t	0.85	8	0.65
	ESG-Consume	t	0.8	24.97	0.59
	Consume-Agriculture	SBB1	0.26	1.43	0.38

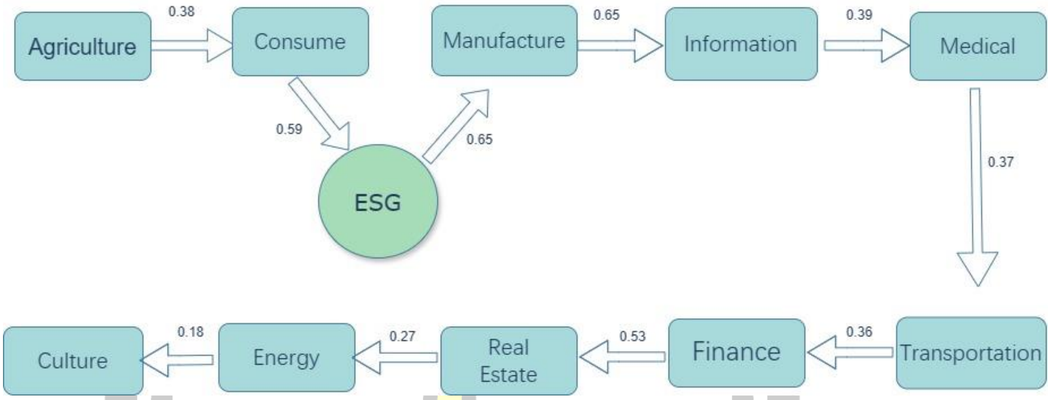


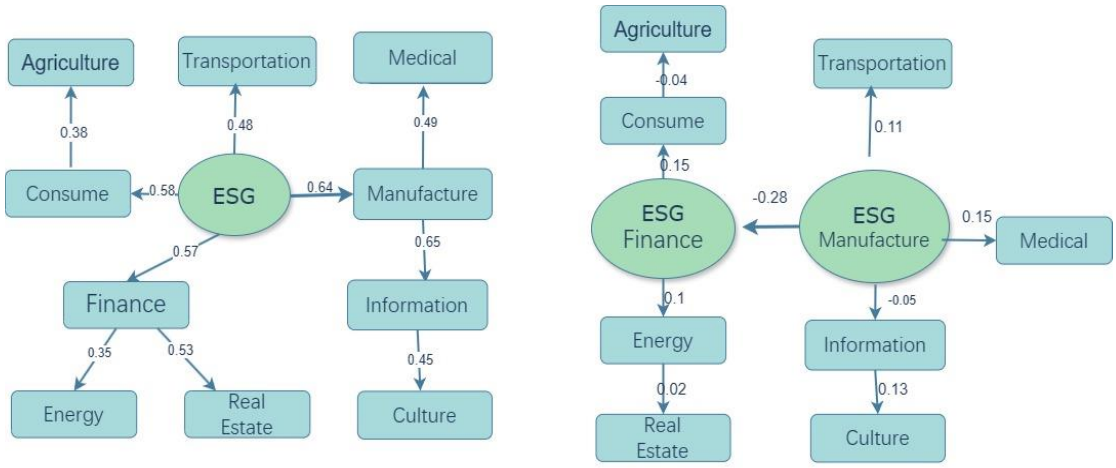
Figure 11: The D-Vine Copula Tree

The conduction chain is represented by the D-Vine Copula Tree. Figure 11 illustrates the upstream-downstream transmission mechanism of the industrial chain. Table 23 shows that the manufacturing-information industry (τ = 0.65) and ESG-manufacturing industry (τ = 0.65) exhibit the highest dependence, indicating that ESG may have a greater impact on the manufacturing industry and that manufacturing is highly correlated with the information industry. This highlights the critical role of information manufacturing in driving the development of emerging industries.

From the transmission process, the upstream agricultural sector first influences the consumption sector. Subsequently, ESG policies are transmitted from consumption to manufacturing, which further extends its influence to the information sector. Additionally, the energy industry affects the real estate industry, which in turn influences the financial sector, ultimately impacting subsequent industries.

Table 24: The Copula Function and τ of R-Vine Copula Tree1

Type	Edge	Copula	Para1	Para2	tau
R-Vine Copula	ESG-Manufacture	t	0.85	8	0.64
	ESG-Finance	BB1	0.59	1.79	0.57
	ESG-Consume	t	0.79	26.62	0.58
	ESG-Transportation	SBB1	0.21	1.74	0.48
	Manufacture-Information	t	0.85	7.23	0.65
	Information-Culture	t	0.65	8	0.45
	Manufacture-Medical	t	0.69	11.57	0.49
	Finance-Real estate	SBB1	0.32	1.84	0.53
	Finance-Energy	SBB1	0.16	1.43	0.35
	Consume-Agriculture	SBB1	0.26	1.43	0.38



R-Vine Copula Tree1

R-Vine Copula Tree2

Figure 12: The R-Vine Copula Tree

Table 24 presents the copula functions and Kendall's τ (τ) values for the R-Vine Copula Tree1. The strongest dependence exists between manufacturing and information industries (τ = 0.65), underlining the central role of information in advancing manufacturing processes. ESG appears to have a moderate impact across multiple industries, with stronger influence on manufacturing and finance. Traditional sectors like energy and real estate show more moderate interdependence with other industries but still play a significant role in affecting finance.

Figure12 refines the hierarchical relationships between industries, emphasizing a layered transmission effect. It highlights consumption and manufacturing as the primary nodes for ESG policy transmission, while other industries are influenced indirectly. In the first layer of Tree 1, the sectors most directly affected by ESG policies are manufacturing, consumption, finance, and transportation, reflecting the alignment with sustainable development goals of consumption-driven growth and manufacturing upgrades. In Tree 2 of the R-Vine Copula, manufacturing and finance emerge as the primary conditions through which ESG impacts propagate to other sectors. The coefficients in the copula structure indicate the direction and strength of these dependencies, further illustrating the nuanced interconnections among industries.

4.1.3.5 Tail Dependency Analysis

Using the tail dependence calculation formula (see Eq. 2.26 and Eq. 2.27), we derived the optimal Copula types, parameter estimates, and tail dependence coefficients based on the Vine-Copula structure. A deeper analysis of tail dependence relationships provides a clearer understanding of the risk transmission and interdependence between the ESG benchmark index and various industries.

Overall, most industries exhibit an asymmetric tail dependence structure, with lower tail dependence coefficients consistently exceeding upper tail coefficients. This indicates that the system faces greater risks during downturns. In terms of coefficient magnitude, manufacturing, finance, real estate, and energy exhibit higher risk values, highlighting their significant roles in tail risk. These industries demand particular attention during market downturns, as they are pivotal in systemic risk events. On the other hand, sectors such as consumption, healthcare, and culture demonstrate lower tail risk, indicating relative stability during market declines.

Table 25: The Tail Dependence of Each Vine Copula

C-Vine Copula			D-Vine Copula			R-Vine Copula		
Edge	Utd	Ltd	Edge	Utd	Ltd	Edge	Utd	Ltd
ESG-Agriculture	0	**0.36**	Culture-Energy	0	**0.23**	ESG-Manufacture	0.41	0.41
ESG-Transportation	0.16	**0.51**	Energy-Real Estate	0.16	0.16	ESG-Finance	0.53	**0.54**
ESG-Medical	0.14	0.14	Real Estate-Finance	0.3	**0.55**	ESG-Consume	0.09	0.09
ESG-Real Estate	0.12	**0.42**	Finance-Transportation	0.06	**0.38**	ESG-Transportation	0.15	**0.51**
ESG-Energy	0.03	**0.48**	Transportation-Medical	0.11	0.11	Manufacture-Information	0.44	0.44
ESG-Information	0.33	**0.48**	Medical-Information	0.1	**0.4**	Information-Culture	0.2	0.2
ESG-Consume	0.52	0.52	Information-Manufacture	0.44	0.44	Manufacture-Medical	0.15	0.15
ESG-Finance	0.52	0.52	Manufacture-ESG	0.41	0.41	Finance-Real estate	0.31	**0.54**
ESG-Manufacture	0.41	0.41	ESG-Consume	0.1	0.1	Finance-Energy	0.04	**0.38**
ESG-Culture	0.02	**0.43**	Consume-Agriculture	0.16	**0.37**	Consume-Agriculture	0.15	**0.37**

From Table 25, we can see that the Vine Copula modeling reveals that ESG factors significantly influence industry interdependencies, particularly in sectors heavily impacted by sustainability regulations and market expectations. The results demonstrate how ESG considerations reshape risk structures within domestic industries, with varying degrees of tail dependence across sectors.

The upper tail dependence (Utd) and lower tail dependence (Ltd) coefficients reveal the co-movement patterns between variables during market upsides and downsides, respectively. These metrics indicate that certain sectors are more sensitive to ESG-related policies and sustainability-driven investment decisions. For instance, Finance-Real Estate (Ltd = 0.54) and ESG-Transportation (Ltd = 0.51) exhibit significant lower tail dependence, suggesting a heightened tendency for synchronized declines during periods of market distress. On the other hand, ESG-Information (Utd = 0.33) and ESG-Consume (Utd = 0.52) demonstrate notable upper tail dependence, reflecting a strong positive co-movement in favorable market conditions.

4.2 Risk Spillover Results

4.2.1 Simulation Results

To evaluate the effectiveness of CoVaR in measuring risk spillovers, a simulation experiment was designed. This part follows the data generation process described in the previous section, using three-dimensional and five-dimensional mixed distribution datasets. Kendall’s τ values of 0.2, 0.5, and 0.7 were set to represent different dependency levels. The ARMA-GARCH model was used to filter the data, the Vine Copula was fitted to capture the dependency structure between variables. Monte Carlo simulation was conducted with 10,000 iterations to estimate Value at Risk (VaR) and Conditional Value at Risk (CoVaR) at the 95% confidence level.

Table 26: The VaR value with Different Dimension and Different τ

Dimension	Variable	τ=0.2	τ=0.5	τ=0.7
d=3	V1	0.012111	0.012023	0.010207
	V2	0.010434	0.010926	0.01109
	V3	0.011336	0.011248	0.01073
d=5	V1	0.009558	0.008891	0.009602
	V2	0.00937	0.0086	0.010281
	V3	0.009193	0.009421	0.009198
	V4	0.010826	0.009897	0.010656
	V5	0.01085	0.0089	0.010494

From Table 26, we can see that in low correlation scenarios (τ = 0.2), increasing the number of dimensions effectively diversifies risk, leading to a decrease in VaR. This indicates that a diversified investment strategy can reduce the extreme loss risk of individual assets, thereby lowering the systemic risk of the entire portfolio. This aligns with the modern portfolio theory, which suggests that investing in low-correlation assets helps mitigate idiosyncratic risk.

However, in high correlation scenarios (τ = 0.7), risk concentration increases, and the dependency structure between assets becomes stronger. As a result, the decline in VaR is limited and may even increase for some variables. This is because highly correlated assets tend to move together under extreme market conditions, amplifying risk across different assets and limiting the risk diversification effect of multi-asset investments. In such cases, a shock to a single market is more likely to propagate throughout the system, exacerbating systemic risk.

Table 27: Define d=3, The CoVaR Value base on Difference Variable

τ	Variable	Var1	Var2	Var3
τ=0.2	Var1	NA	0.009701	0.003938
	Var2	0.009748	NA	0.003113
	Var3	0.00412	0.0066	NA
τ=0.5	Var1	NA	0.003253	0.002934
	Var2	0.002561	NA	0.002763
	Var3	0.00271	0.001886	NA
τ=0.7	Var1	NA	0.002363	0.002073
	Var2	0.003028	NA	0.002849
	Var3	0.002567	0.002341	NA

From Table 27, for d=3, when τ increases from 0.2 to 0.7, CoVaR values generally decrease, meaning as dependence strengthens, the conditional risk spillover becomes more stable. The highest CoVaR values appear when τ=0.2, particularly between Var1-Var2 (0.009701), Var2-Var1 (0.009748), and Var2-Var3 (0.0066). This suggests that at low dependence levels, the risk transmission between these variables is more uncertain. When τ=0.7, CoVaR values are much lower (mostly below 0.003), indicating that at high dependence, risk transmission stabilizes.

Table 28: Define d=5, The CoVaR Value base on Difference Variable

τ	Variable	Var1	Var2	Var3	Var4	Var5
τ=0.2	Var1	NA	0.005015	0.004421	0.004855	0.003978
	Var2	0.004703	NA	0.004209	0.003252	0.002685
	Var3	0.004114	0.004446	NA	0.003917	0.004808
	Var4	0.003381	0.003999	0.005437	NA	0.005781
	Var5	0.002317	0.00379	0.004005	0.003197	NA
τ=0.5	Var1	NA	0.002815	0.00237	0.002165	0.002984
	Var2	0.003846	NA	0.002557	0.002553	0.004146
	Var3	0.00234	0.00317	NA	0.002991	0.00204
	Var4	0.003277	0.003004	0.002484	NA	0.002542
	Var5	0.002256	0.00321	0.002505	0.003183	NA
τ=0.7	Var1	NA	0.00181	0.00255	0.002725	0.00165
	Var2	0.003756	NA	0.002188	0.002664	0.002618
	Var3	0.002273	0.00201	NA	0.002606	0.002387
	Var4	0.002007	0.003304	0.002732	NA	0.002874
	Var5	0.00211	0.001956	0.004328	0.003384	NA

From Table 28, when d=5, as dependence increases (τ=0.2 → 0.7), CoVaR values generally decrease. For τ=0.2, the highest CoVaR values appear between Var4-Var5 (0.005781) and Var3-Var4 (0.005437), meaning these variables have stronger risk spillovers at low dependence. At τ=0.7, most CoVaR values fall below 0.003, which suggests that when variables have stronger dependence, their risk interaction becomes more predictable and stable.

Specifically, VaR measures the standalone risk level of an asset or portfolio, whereas CoVaR reflects the extreme loss level of a specific asset or portfolio given that a systemic risk event has occurred. When market correlations are high (τ = 0.7), the variation in CoVaR becomes more pronounced, suggesting that systemic shocks intensify the extreme losses of individual assets. This confirms that in highly dependent structures, the risk transmission mechanism is more complex, and systemic shocks have a greater impact.

Therefore, in risk management practice, relying solely on VaR may underestimate the impact of extreme market events, whereas CoVaR provides a more systemic perspective on risk assessment. Particularly in high-correlation market environments, CoVaR is more effective in measuring systemic risk spillovers in financial systems.

4.2.2 Application Results of RCEP Countries' Risk Spillover

To study the risk spillover relationships among RCEP countries, this research utilizes real stock market data from RCEP countries. Based on the results of the R-Vine Copula model and Monte Carlo simulations, we calculate the VaR and CoVaR values to analyze the spillover pathways of risk across different countries.

Table 29: The VaR for Each Country at Different Confidence Levels

Countries	90%	95%	99%
China	0.1011	0.0502	0.0103
Thailand	0.1009	0.0492	0.0105
Malaysia	0.1014	0.0496	0.0087
Japan	0.1032	0.0501	0.0099
Korea	0.0992	0.0466	0.0096
Singapore	0.1036	0.0540	0.0115
New Zealand	0.0971	0.0507	0.0113
Australia	0.0963	0.0487	0.0111
Philippines	0.0958	0.0491	0.0103
Indonesia	0.1018	0.0519	0.0107
Vietnam	0.0995	0.0513	0.0101

From Table 29, Singapore, Japan, and Malaysia exhibit higher VaR values at the 90% confidence level, reflecting their active financial markets and higher volatility. Singapore, as Southeast Asia's financial hub, and Japan, the world's third-largest economy, naturally experience greater market fluctuations.

At the 99% confidence level, Malaysia (0.0087), Japan (0.0099), and South Korea (0.0096) register the lowest VaR values. This suggests that their relatively mature market structures and strong regulatory frameworks contribute to enhanced stability and risk management capabilities, thereby reducing extreme loss potential.

Table 30: The CoVaR of Each Country

Countries	China	Thailand	Malaysia	Japan	Korea	Singapore	New Zealand	Australia	Philippines	Indonesia	Vietnam
China	-	0.0132	0.0143	0.024	0.017	0.0277	0.0126	0.0158	0.0183	0.005	0.0131
Thailand	0.015	-	0.0042	0.009	0.004	0.0242	0.0059	0.0042	0.0066	0.0042	0.0083
Malaysia	0.02	0.0067	-	0.007	0.005	0.0174	0.01	0.0084	0.0059	0.0058	0.0108
Japan	0.012	0.005	0.0057	-	0.003	0.0226	0.0101	0.0033	0.0042	0.0042	0.0084
Korea	0.011	0.0076	0.0058	0.007	-	0.0295	0.0109	0.014	0.0042	0.0066	0.0083
Singapore	0.007	0.0058	0.0074	0.007	0.022	-	0.0546	0.0166	0.0336	0.0099	0.0252
New Zealand	0.02	0.0083	0.0122	0.007	0.013	0.0597	-	0.0042	0.0033	0.0163	0.0081
Australia	0.017	0.005	0.005	0.005	0.007	0.0226	0.0084	-	0.0074	0.0066	0.0092
Philippines	0.035	0.0059	0.0042	0.009	0.005	0.0293	0.0076	0.0108	-	0.0067	0.0108
Indonesia	0.017	0.005	0.0083	0.009	0.013	0.0242	0.0075	0.0142	0.0033	-	0.0141
Vietnam	0.007	0.0075	0.0066	0.008	0.004	0.0242	0.0084	0.0066	0.0066	0.005	-

From Table 30, by comparing the CoVaR values, we conclude that China, Singapore, and Japan serve as key risk transmission hubs in the RCEP region, exhibiting relatively high CoVaR values. These countries significantly impact other markets during financial market fluctuations.

China's CoVaR values with Japan (0.0124), Korea (0.0112), Malaysia (0.0202), and Singapore (0.0277) indicate that fluctuations in China's financial market have substantial effects on both East Asian and ASEAN economies. Singapore's CoVaR values with Korea (0.0295), Australia (0.0226), and New Zealand (0.0597) highlight its pivotal role as a financial center, transmitting risk across the Asia-Pacific region. The strong dependence between New Zealand and Singapore suggests that trade and investment ties amplify financial spillovers.

Moreover, Japan is both a risk recipient and a risk transmitter, reflecting strong financial linkages within East Asia. Thailand's CoVaR values with China (0.0146), Malaysia (0.0067), and Singapore (0.0242) suggest that Thailand acts as a regional conduit for risk spillover, particularly within ASEAN. This supports the notion of two primary risk spillover pathways: The first is the East Asia-Southeast Asia transmission chain, with China, Japan, Korea, and Singapore as major nodes, and the second is the Asia-Pacific financial spillover chain, linking Singapore, Australia, and New Zealand.

Based on the above analysis, we can summarize the major risk spillover pathways in RCEP countries as follows:

(1) China → Korea→ Japan→ Singapore →Thailand→ Malaysia→ Philippines → Vietnam→ Indonesia.

(2) Singapore → New Zealand → Australia →Korea→ Japan→ Thailand. → Philippines→ Vietnam→ Indonesia.

The first pathway reflects the dependency relationship between East Asian and Southeast Asian markets, with China, Japan, Korea, and Singapore as key nodes in the risk spillover process. The second pathway highlights the risk interconnection within the Asia-Pacific market, where Singapore and China play central roles in transmitting financial shocks—Singapore as a regional financial hub and China as a dominant economic force. Both Singapore and China serve as the primary sources of risk transmission, with their financial market fluctuations impacting the entire RCEP system.

4.2.3 Application Result of Chinese Industries Risk Spillover

To investigate the hierarchical spillover effects of risk, this study utilizes the R-Vine Copula model combined with Monte Carlo simulation. By generating 10,000 sets of return series, the losses of each industry under various scenarios were calculated. Based on these simulations, the Value at Risk (VaR) and Conditional Value at Risk (CoVaR) for each industry were estimated, providing insights into the risks faced by different industries under extreme market conditions.

4.2.3.1 Value at Risk (VaR)

VaR is a measure of the maximum loss a portfolio can suffer at a certain level of confidence over a given period of time. Table 31 below shows VaR values for each industry at different confidence levels.

Table 31: The VaR of Various Industries at Different Confidence Levels

Industry	90%	95%	99%
ESG	0.099784	0.050948	0.010108
Energy	0.102693	0.051622	0.008934
Manufacture	0.098758	0.053024	0.008546
Finance	0.102172	0.048574	0.009425
Real estate	0.101581	0.049234	0.010411
Consume	0.100427	0.048899	0.010303
Agriculture	0.102488	0.053974	0.010529
Medical	0.095649	0.049394	0.008874
Transportation	0.103161	0.050401	0.010638
Information	0.098758	0.054005	0.009939
Culture	0.102865	0.048429	0.009647

As shown in Table 31, at a lower confidence level (90%), the Value at Risk (VaR) values across industries exhibit a narrow range (0.099–0.103). This indicates that under mild market fluctuations, the maximum potential loss across industries remains relatively low and similar, suggesting minimal systemic risk transmission between industries at this stage.

As the confidence level rises to 95%, Energy (0.0516) and manufacturing (0.053) display slightly higher VaR values compared to others. This suggests that these industries are more sensitive to market fluctuations under moderate financial stress. The increased risk may stem from their strong external dependencies, such as energy price volatility or fluctuations in raw material costs affecting manufacturing.

Under extreme market conditions (99% confidence level), VaR values decline significantly across all industries, ranging from 0.008 to 0.01. This suggests that potential losses in extreme events are limited, possibly due to built-in market protection mechanisms or industry resilience. For instance, the maximum loss in the energy sector at the 99% confidence level is 0.8%, whereas the real estate sector reaches 1.04%. The relatively lower VaR for the energy sector may be attributed to its long-term market stability and price adjustment mechanisms, while the higher VaR for the real estate sector could reflect its strong dependence on liquidity and capital markets.

Industries with higher VaR values—such as energy, manufacturing, and real estate—should prioritize strengthening risk management strategies. This may include implementing price hedging mechanisms, enhancing supply chain resilience, and optimizing capital structures to improve their ability to absorb shocks. In the context of ESG policies, promoting green financial instruments can help these industries reduce financing costs and support their transition toward sustainability, mitigating risks under extreme market conditions. Additionally, fostering cross-industry collaboration—leveraging the resilience of consumer, information, and cultural sectors—can enhance technological synergy and market integration, thereby improving the overall economy’s ability to withstand financial stress.

4.2.3.2 CoVaR Analysis

CoVaR refers to the risk of an individual asset or portfolio when other assets or portfolios are at the VaR level, reflecting the contagion effect of systemic risk. The following CoVaR matrix provides insights into the risk transmission paths between different industries, helping to identify which industries have a stronger risk dependence relationship. A larger CoVaR value indicates that one industry has a stronger risk transmission effect on other industries under extreme adverse conditions, while a relatively smaller CoVaR value suggests that an industry has a smaller risk contagion effect on others. By observing the CoVaR values, key risk transmission paths can be identified. Analyzing industries with higher column values helps assess their sensitivity to systemic risk.

Table 32: The CoVaR of Each Industries

Industries	ESG	Energy	Manufacture	Finance	Real estate	Consume	Agriculture	Medical	Transportation	Information	Culture
ESG	-	0.303	0.352	0.294	0.396	0.305	0.45	0.274	0.299	0.295	0.588
Energy	0.35	-	0.722	0.33	0.297	0.463	1.031	1.107	0.446	0.555	0.587
Manufacture	0.38	0.48	-	0.41	0.3	0.36	0.5	0.38	0.28	0.29	0.28
Finance	0.25	0.351	0.303	-	0.288	0.377	0.393	0.634	0.225	0.473	0.589
Real estate	0.27	0.422	0.468	0.247	-	0.642	0.95	0.653	0.285	0.597	0.454
Consume	0.42	0.695	0.313	0.377	0.655	-	0.371	0.49	0.449	0.834	0.577
Agriculture	0.43	1.121	0.938	0.719	1.109	0.213	-	0.616	0.438	0.77	1.024
Medical	0.25	0.989	0.365	0.41	0.376	0.335	0.623	-	0.357	0.381	0.48
Transportation	0.24	0.372	0.29	0.356	0.45	0.304	0.443	0.403	-	0.374	0.361
Information	0.33	0.928	0.18	0.292	0.488	0.646	0.984	0.346	0.325	-	0.415
Culture	0.49	0.888	0.33	0.451	0.641	0.364	0.611	0.581	0.496	0.328	-

See in Table 32, the CoVaR values between ESG and Agriculture (0.45), Culture (0.588), Consumption (0.305), and Manufacturing (0.352) are relatively high, indicating a strong dependency relationship between ESG development and these industries. The Agriculture sector exhibits significant risk spillover effects on Energy (1.031), Real Estate (0.95), Information (0.984), and Culture (1.024). Similarly, the Energy sector has substantial risk spillover effects on Agriculture (1.121) and Medical (1.107), suggesting that systemic risks in the energy market, such as oil price fluctuations and energy supply chain disruptions, could have a significant impact on both the agricultural and medical sectors. Given the strong risk spillover effects in the Energy, Agriculture, and Real Estate industries, these sectors should be prioritized in systemic risk monitoring.

Based on the CoVaR matrix, combined with the C-Vine, D-Vine, and R-Vine Copula models, we can assess the risk transmission effects between industries and identify industries with strong risk dependence. According to this, we draw the risk spillover path graph as follow:

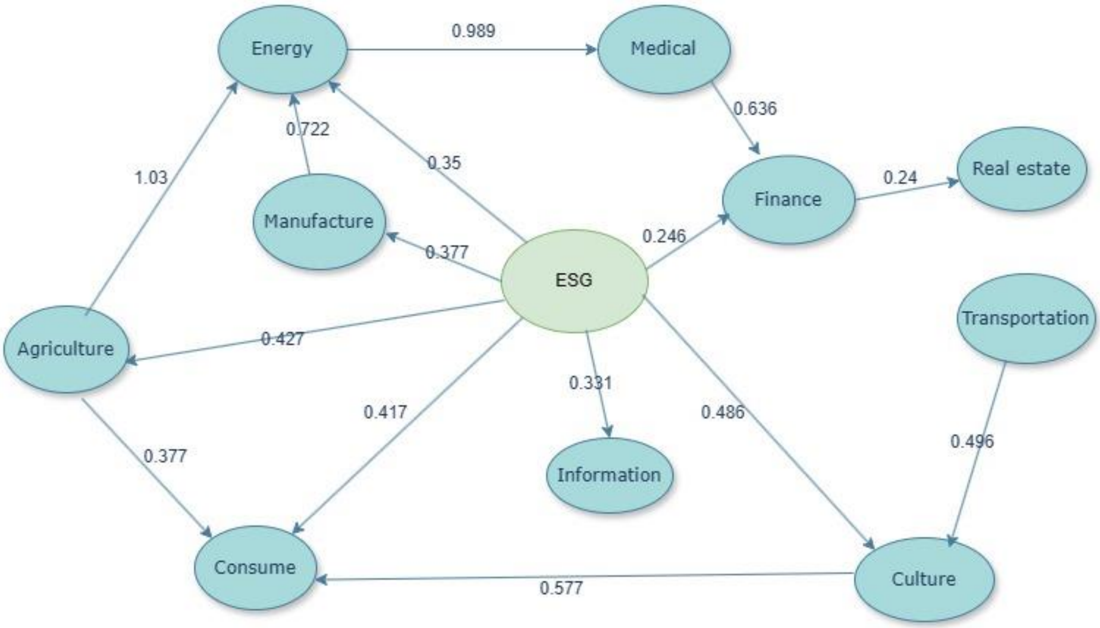


Figure 13: Risk Spillover Pathways

From Figure 13, it is evident that ESG policies, as a central guiding factor, exert significant influence on the entire system. When ESG policies face extreme conditions, they generate substantial spillover effects on energy (0.35), manufacturing

(0.377), consumer industries (0.417), agriculture (0.427), and cultural industries (0.486).

From the perspective of the industrial chain structure (D-vine), agriculture, as the upstream sector of the chain, acts as the primary pathway of transmission. Agriculture impacts downstream industries, including finance, real estate, healthcare, manufacturing, information, and culture, via cost linkages (energy, 1.031) and demand chains (consumer, 0.371).

In terms of conditional dependence structure (R-vine), ESG primarily influences manufacturing (0.377) and subsequently affects energy demand (0.722), real estate (0.468), and healthcare (0.365), highlighting the pivotal role of manufacturing as a secondary central node in the industrial system.

The energy sector demonstrates significant risk spillover effects on healthcare (1.107) and real estate (0.950), indicating that fluctuations in energy can cause widespread systemic impacts on sectors reliant on resource inputs or infrastructure. Real estate serves as a mediator in risk transmission, influencing consumption through asset price fluctuations and liquidity constraints.

The consumer, transportation, and cultural industries exhibit higher resilience and strong risk resistance, with no substantial spillover effects observed.

By integrating the Vine Copula dependence structure and CoVaR values, a risk spillover pathway diagram has been constructed, illustrating the transmission paths of risk between ESG and various industries. This diagram reveals the hierarchical dependencies and interconnectedness of industries, providing deeper insights into systemic risk propagation.

Chapter 5
Conclusion and Discussion

5.1 Conclusion

This study provides an in-depth analysis of the interdependence between financial markets and industrial structures among RCEP countries from a dependence structure perspective. By integrating the Vine Copula and CoVaR methods, we analyze mutual dependence relationships using the Vine Copula model and measure extreme risk spillover effects through the CoVaR approach. This study develops an analytical framework for industrial structure and risk spillover under the ESG framework. First, we establish a theoretical foundation for dependence structures and risk spillovers and conduct simulation experiments to validate the effectiveness of Vine Copula in capturing asymmetric dependence and the accuracy of CoVaR in measuring extreme risk spillovers. Subsequently, we utilize index data from RCEP member countries and China's industrial structure under the ESG framework to analyze the impact of the RCEP agreement on dependence structures and risk transmission mechanisms. Through a systematic analysis from both horizontal and vertical perspectives, this study reveals the complex interdependence and risk transmission characteristics in international and domestic markets at multiple levels and from different angles. The primary findings of this study are as follows:

5.1.1. Dependence Structure and Risk Spillover Paths in RCEP Countries

(1) Dependence Structure Change. Through a horizontal comparison of RCEP member countries, the study finds that the RCEP agreement has significantly enhanced the economic interdependence among member states. The implementation of RCEP has not only promoted regional trade and investment flows but has also deepened the interdependence structure among member countries through the linkage effects of financial markets. Moreover, the interdependence structure of the markets has shown a multipolar characteristic, transitioning from a structure dominated by South Korea to a multipolar one centered around South Korea and Australia.

(2) Risk Spillover Paths. The identification of risk spillover paths indicates that China, South Korea, and Singapore play key roles in regional risk transmission, while Southeast Asian countries (Thailand, Malaysia, Vietnam and Indonesia) tend to be more reactive to the risks. The risk spillover effects exhibit a dual transmission characteristic, with two main pathways.

Path 1: China → Korea → Japan → Singapore → Thailand → Malaysia → Philippines → Vietnam → Indonesia, reflecting the regional economic radiation effect centered around China.

Path 2: Singapore → New Zealand → Australia →Korea→ Japan→ Thailand. → Philippines→ Vietnam→ Indonesia. This path highlights the risk linkage between financial centers (Singapore) and developed economies (Japan, Australia).

Overall, RCEP has strengthened economic ties among its members, fostering regional cooperation. However, it has also increased the potential for risk propagation. Given the dynamic nature of financial markets and the evolving dependence structure, risk transmission has become more multi-polarized and networked. There is an urgent need to enhance regional financial regulatory cooperation and establish cross-border risk warning mechanisms to mitigate the potential risks associated with economic integration and implement more effective policy responses.

5.1.2. Industrial Volatility Spillovers and the Impact of ESG Policies

A vertical comparison of China’s industrial structure under the ESG framework reveals that industrial volatility is closely linked to ESG benchmark indices.

(1) ESG policies play a pivotal role in risk transmission across industries. The C-Vine Copula analysis indicates that ESG benchmark indices occupy a central position in the industrial risk network, demonstrating the significant impact of ESG policies on industrial structure adjustments and risk transmission. The D-Vine Copula analysis identifies agriculture, manufacturing, and consumer sectors as upstream industries with strong spillover effects on downstream sectors such as energy and technology. The R-Vine Copula model further describes the intricate interdependencies among industries.

(2) Systemic risk is more pronounced during economic downturns. Tail dependence analysis indicates that risk contagion intensity is significantly higher during economic downturns than in periods of economic expansion, suggesting that extreme risk events are more likely to trigger chain reactions across industries. CoVaR estimates identify key risk spillover points, emphasizing that agriculture and energy industries are primary sources of systemic risk. This finding aligns with the vulnerabilities in the global supply chain and the ongoing energy transition. The results provide empirical support for optimizing industrial structures and enhancing supply chain resilience.

5.1.3. Policy Implications

(1) Regional Cooperation. Strengthening financial regulatory coordination among RCEP member countries is essential to establishing cross-border risk warning and emergency response mechanisms. Additionally, promoting green finance cooperation should be a priority, encouraging member states to invest in ESG-related technological innovation. By fostering sustainable investment and enhancing corporate ESG performance, regional economic stability can be reinforced.

(2) Industrial Policy and Supply Chain Resilience. Optimizing industrial structures and enhancing supply chain resilience, particularly in the agricultural and energy sectors, is crucial. Policymakers should implement differentiated ESG policies to guide high-risk industries toward green and low-carbon transitions. Promoting industrial collaboration and technological innovation will facilitate structural optimization and reinforce supply chain resilience, mitigating extreme risk spillover effects. In an era of increasing global economic interdependence, policymakers must adopt proactive measures, innovative analytical approaches, and enhanced coordination mechanisms to address the challenges posed by regional economic integration and sustainable development.

5.2 Discussion

5.2.1 Theoretical Contributions and Practical Implications

This study integrates Vine Copula and CoVaR methodologies to construct an innovative analytical framework, providing methodological support for investigating complex dependence structures and risk spillover effects. Specifically, the contributions are as follows:

(1) Advancing Dependence Structure Modeling. While traditional financial risk models often assume linear dependencies, this study demonstrates that Vine Copula offers greater flexibility in capturing asymmetric and nonlinear relationships in financial and commodity markets, enhancing the adaptability of Copula models to dynamic financial environments. This methodological advancement contributes to the broader literature on systemic risk assessment (Adrian & Brunnermeier, 2016) and provides a robust empirical tool for policymakers and investors.

(2) Bridging ESG Framework with Risk Spillover Analysis. Unlike conventional risk spillover studies that focus solely on financial contagion, this study expands the research scope by incorporating the ESG framework. This contribution aligns with emerging literature that emphasizes the role of sustainability factors in financial stability (Pedersen et al., 2021; Bolton et al., 2021). Our findings provide new insights into how green finance policies influence sectoral dependence structures and risk transmission.

(3) Implications for RCEP Economic Cooperation. Our findings offer empirical support for economic cooperation policies within RCEP member countries, particularly regarding regional financial stability and industrial coordination. The study highlights the significance of energy-commodity market integration, which could guide trade policies and regional investment strategies.

(4) Implications for China's Industrial Transition. The research reveals that ESG policies play a pivotal role in industrial transformation, especially in mitigating cross-sectoral financial risks. Given China’s "dual-carbon" (carbon peak and neutrality) strategy, our results provide quantitative evidence for policymakers, reinforcing the need for sector-specific ESG policies to enhance industrial resilience.

5.2.2 Research Limitations

(1) Data and Model Limitations. The accuracy of our findings depends on the quality and length of the sample data. Although we employ financial data, the availability of historical ESG indicators remains limited. Future studies could enhance model robustness by incorporating longer time-series datasets and alternative data sources, such as real-time ESG disclosures and ESG scores.

(2) Model Assumptions and Estimation Bias: The results may be sensitive to specific assumptions about marginal distributions and Copula families. Further research could explore semi-parametric EVT and GPD for tail modeling or non-parametric approaches (machine-learning) to mitigate assumption dependency.

(3) Scope and Depth of Research: This study primarily focuses on macro-level market interactions, overlooking firm-level ESG performance and corporate risk spillover mechanisms. Future research could integrate firm-level financial data (e.g., ESG scores, credit spreads) to examine how corporate ESG adoption influences systemic risk propagation.

(4) Long-Term Effects of RCEP Policy Implementation: Given that RCEP is still in its early stages, our analysis may not fully capture the long-term dynamic effects of trade liberalization on market dependencies. Employing state-space models or dynamic Copula approaches could offer deeper insights into the gradual evolution of risk spillover mechanisms post-RCEP implementation.

5.2.3. Research Directions in the Future

(1) Macroeconomic and Geopolitical Risk Integration. Future studies should incorporate additional macroeconomic indicators (GDP growth, inflation, interest rate volatility) and geopolitical risk factors (supply chain disruptions, trade wars) to provide a more comprehensive risk transmission framework.

(2) Comparative Studies on Other Regional Agreements. Expanding the analysis to other regional economic agreements, such as CPTPP and EU trade policies, would allow for cross-regional comparisons of trade-driven financial dependencies and risk transmission patterns. With the advancement of AI-driven financial modeling, future research could leverage deep learning techniques to uncover hidden dependence structures in high-dimensional financial networks.

In summary, this study integrates advanced dependence modeling, CoVaR estimation methods, and macroeconomic risk factors to contribute to the fields of financial contagion, ESG risk analysis, and regional economic integration. By constructing a comprehensive analytical framework, we provide valuable insights into the mechanisms of cross-market risk spillovers under extreme conditions. Despite certain limitations related to data scope and modeling assumptions, our framework lays a solid foundation for future research. Moving forward, studies should expand datasets, refine model assumptions, and incorporate AI-driven approaches to further enhance the understanding of complex market interdependencies and risk transmission mechanisms in an increasingly dynamic global economy.

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APPENDIX A

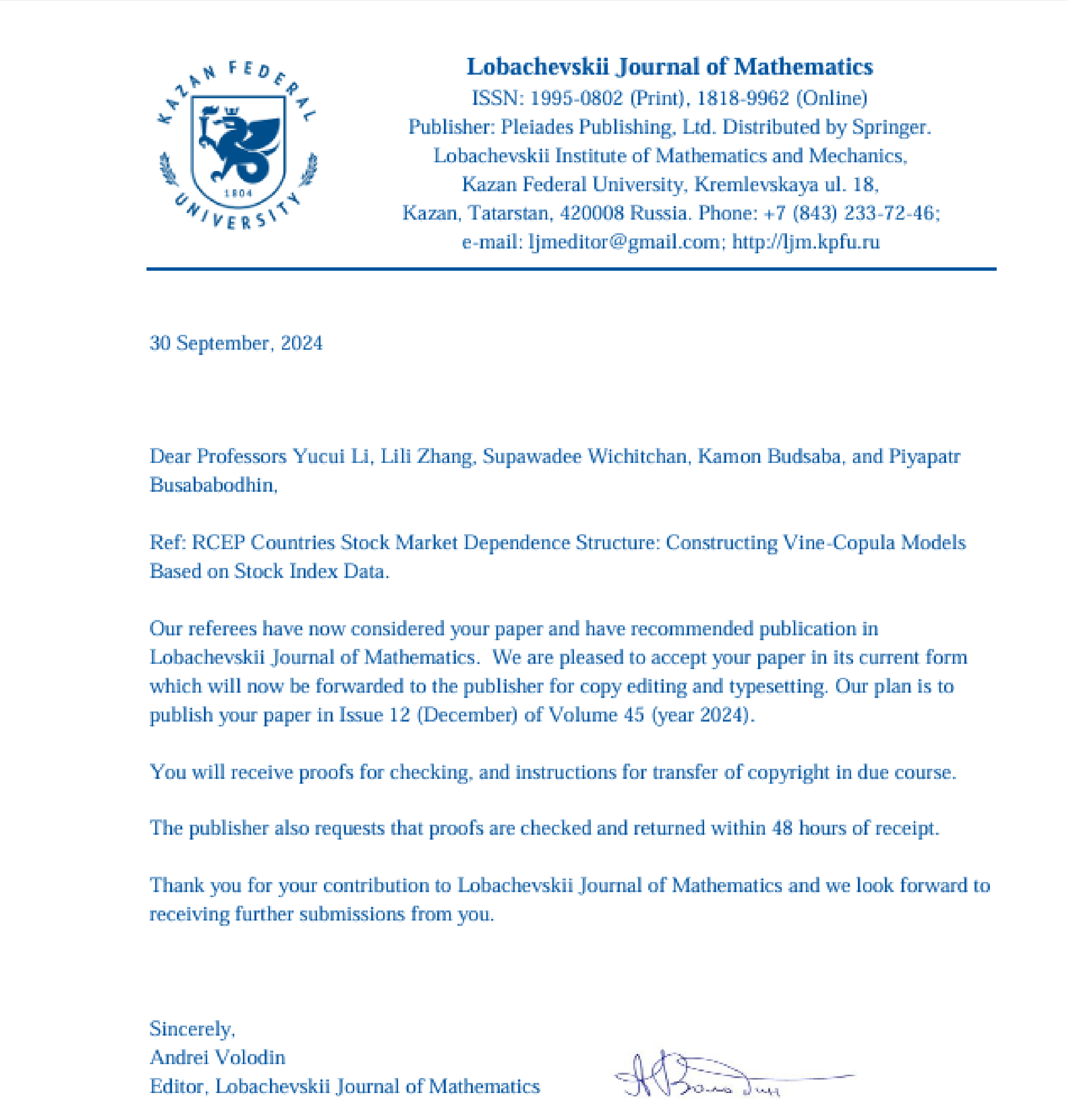
```
###Main Programs###

library(tidyverse)
library(quantmod)
library(rugarch)
library(rvinecopulib)
library(copula)
library(VineCopula)
library(tseries)
library(forecast)
library(TSP)

data <- read.csv("total_EN.csv")
data$date <- as.Date(data$date, format = "%Y-%m-%d")
data_num <- data %>% select(-date)
data_log <- apply(log(data_num), 2, diff) %>% as_tibble() %>% mutate_all(~ . *
    100)

ggplot(data_log_long, aes(x = Time, y = Log_Returns, color = Industry)) +
  geom_line() +
  labs(title = "Log Returns Over Time", x = "Time", y = "Log Returns (%)") +
  theme_minimal()

stock_stats <- data.frame(
  Mean = apply(data_log, 2, mean),
  SD = apply(data_log, 2, sd),
  Skewness = apply(data_log, 2, skewness),
  Kurtosis = apply(data_log, 2, kurtosis)
)
print(stock_stats)

adf_test_results <- sapply(data_log, adf.test)
jb_test_results <- sapply(data_log, jarque.bera.test)
box_test_results <- sapply(data_log, function(x) Box.test(x, lag = 20, type =
    "Ljung-Box", fitdf = 0))

fit_arima_garch <- function(series) {
  arima_model <- auto.arima(series, trace = TRUE, test = "adf", ic = "aic")
  order_best <- c(arima_model$arma[1], arima_model$arma[2])

  garch_spec <- ugarchspec(
    variance.model = list(model = "eGARCH", garchOrder = c(1, 1)),
    mean.model = list(armaOrder = order_best, include.mean = TRUE),
    distribution.model = "sstd"
  garch_fit <- ugarchfit(spec = garch_spec, data = as.matrix(series))
  return(residuals(garch_fit, standardize = TRUE))
```

```
}
# Fit ARMA-GARCH model
out_ok <- NULL
for (k in 1:ncol(data_log)) {
  residuals_z <- fit_arima_garch(data_log[, k])
  out_ok <- cbind(out_ok, residuals_z)
}
colnames(out_ok) <- colnames(data_log)

u <- pobs(out_ok)
ks_results <- apply(u, 2, function(col) ks.test(col, "punif"))

# Fit R_Vine Copula
vine_copula_model <- RVineStructureSelect(u, familyset = NA, type = "RVine",
        treecrit = "tau", cores = cores)
print(vine_copula_model)
summary(vine_copula_model)

# Fit C-Vine Copula
C_vine_copula_model <- RVineStructureSelect(u, familyset = NA, type =
        "CVine", treecrit = "tau", cores = cores)
print(C_vine_copula_model)
summary(C_vine_copula_model)
#plot(C_vine_copula_model)

#Fit D-vine copula
d <- ncol(u)
M <- 1 - abs(TauMatrix(u))
hamilton <- insert_dummy(TSP(M), label = "cut")
sol <- solve_TSP(hamilton, method = "repetitive_nn")
order <- cut_tour(sol, "cut")

DVM <- D2RVine(order, family = rep(0, d * (d - 1) / 2), par = rep(0, d * (d - 1) /
        2))
d_vine_model <- RVineCopSelect(data = u, familyset = NA, Matrix =
        DVM$Matrix)
print(d_vine_model)
summary(d_vine_model)
plot(d_vine_model)

# Simulation VaR base on R-Vine Copula
set.seed(1234)

calculate_var <- function(data, alpha = 0.01) {
  var <- apply(data, 2, function(col) {
    quantile(col, probs = alpha)
  })
```

```
  return(var)
}

sim_data <- RVineSim(N = 10000, RVM = R_vine_copula_model)
var_results_sim <- calculate_var(sim_data)

print(var_results_sim)
#write.csv(var_results_sim, "var_results_sim.csv")



# CoVaR, N=10000
calculate_covar <- function(u, vine_copula_model, var_index, cond_index, alpha = 0.05) {
  sim_data <- RVineSim(N = 10000, RVM = vine_copula_model)
  cond_quantile <- quantile(sim_data[, cond_index], probs = alpha)
  conditional_data <- sim_data[sim_data[, cond_index] <= cond_quantile, var_index]
  covar <- quantile(conditional_data, probs = alpha)
  return(covar)
}

covar_results <- matrix(NA, ncol = ncol(u), nrow = ncol(u))
for (i in 1:ncol(u)) {
  for (j in 1:ncol(u)) {
    if (i != j) {
      covar_results[i, j] <- calculate_covar(u, vine_copula_model, var_index = i, cond_index = j)
    }
  }
}
colnames(covar_results) <- colnames(data_log)
rownames(covar_results) <- colnames(data_log)
print(covar_results)
write.csv(covar_results, "covar_results_sim.csv")
```

APPENDIX B

B.1 The 1st Manuscript



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Lobachevskii Institute of Mathematics and Mechanics,
Kazan Federal University, Kremlevskaya ul. 18,
Kazan, Tatarstan, 420008 Russia. Phone: +7 (843) 233-72-46;
e-mail: ljmeditor@gmail.com; http://ljm.kpfu.ru

30 September, 2024

Dear Professors Yucui Li, Lili Zhang, Supawadee Wichitchan, Kamon Budsaba, and Piyapatr Busababodhin,

Ref: RCEP Countries Stock Market Dependence Structure: Constructing Vine-Copula Models Based on Stock Index Data.

Our referees have now considered your paper and have recommended publication in Lobachevskii Journal of Mathematics. We are pleased to accept your paper in its current form which will now be forwarded to the publisher for copy editing and typesetting. Our plan is to publish your paper in Issue 12 (December) of Volume 45 (year 2024).

You will receive proofs for checking, and instructions for transfer of copyright in due course.

The publisher also requests that proofs are checked and returned within 48 hours of receipt.

Thank you for your contribution to Lobachevskii Journal of Mathematics and we look forward to receiving further submissions from you.

Sincerely,
Andrei Volodin
Editor, Lobachevskii Journal of Mathematics

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RCEP Countries Stock Market Dependence Structure: Constructing Vine-Copula Models Based on Stock Index Data

Yucui Li[1*], **Lili Zhang**[2**], **Supawadee Wichitchan**[1***],
Kamon Budsaba[3****], and **Piyapatr Busababodhin**[#1*****]

(Submitted by A. I. Volodin)

[1] *Department of Mathematics, Faculty of Science, Mahasarakham University,*
Maha Sarakham, 44150 Thailand

[2] *College of Information and Communication, National University of Defense Technology,*
Wuhan, 430000 China

[3] *Department of Mathematics and Statistics, Faculty of Science and Technology, Thammasat University,*
Rangsit Center Pathumthani, 12120 Thailand

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Abstract—The signing and implementation of Regional Comprehensive Economic Partnership (RCEP), being one of the largest free trade agreements, had multifaceted impacts on the participating countries. In the realm of regional economic cooperation, it has strengthened cross-border trade and collaboration, fostering increased economic integration and providing nations with more opportunities for economic growth. In the financial sector, financial cooperation has deepened, and the interconnectivity of stock markets among countries has grown. While aiding collective responses to financial crises and challenges, it has also created conditions for the contagion and spread of financial risks. This study utilized time-series data of stock indices from member countries in RCEP to examine the dependence structure. Initially, the study measures the volatility effects of stock markets using Ljung–Box test and then employed an ARMA-EGARCH model to filter time series data of stock indices. And then we obtained the marginal distributions of each variable from the standardized residuals. For joint distribution, We constructed a Vine Copula model to analyze the dependence structure. Comparing the τ of Vine Copula through pre-RCEP and post-RCEP implementation, we found that RCEP enhanced stock market linkages among member countries. Meanwhile, the implementation of the RCEP has altered the dependence structure among the member countries. South Korea has emerged as a central node within this structure, while Japan's position has been overtaken by Australia. This indicates that RCEP has exerted a notable influence on the financial markets of its member countries, a shift that has been effectively captured by the Vine Copula model.

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[*] E-mail: `1056786125@qq.com`
[**] E-mail: `lilzhang@126.com`
[***] E-mail: `supawadee.wi@msu.ac.th`
[****] E-mail: `kamon@mathstat.sci.tu.ac.th`
[*****] E-mail: `piyapatr.b@msu.ac.th`
[#] The corresponding author.

1. INTRODUCTION

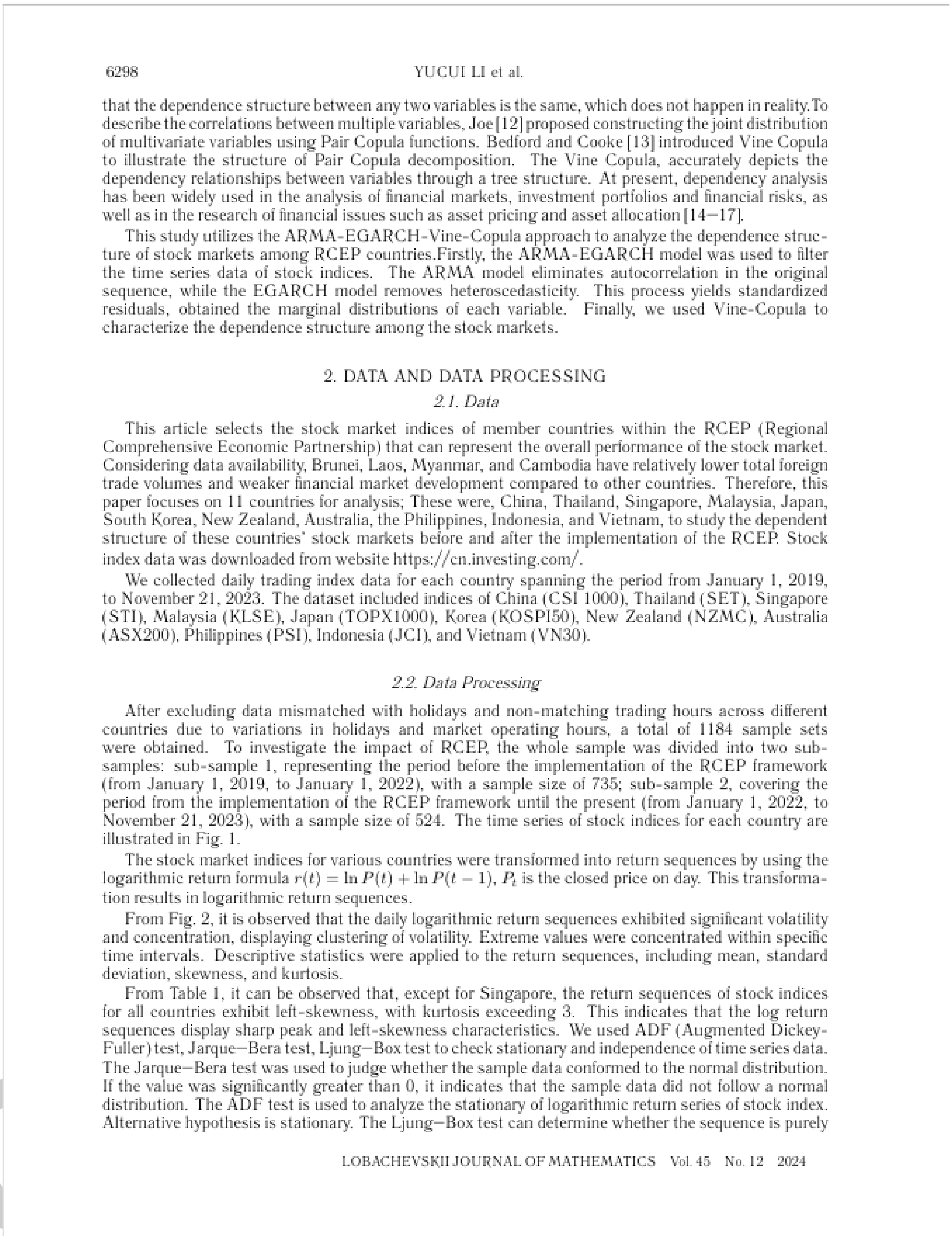
On November 15, 2020, the leaders of the ten ASEAN countries, along with China, Japan, South Korea, Australia and New Zealand, signed the Regional Comprehensive Economic Partnership (RCEP) during the East Asia Cooperation Leaders' Meeting. The signing had far-reaching implications for member countries and the global economy. It strengthened the ties among member countries, promoted international trade and cross-border investments, reduced tariffs, and broke down trade barriers, achieving trade liberalization. The connections in the financial markets deepen, and the movement of factors increased the possibility of financial risks transmitting between markets.

When a country undergoes significant fluctuations, the volatility and risk may spread to another country, triggering abnormal fluctuations in financial markets. Due to the diverse economic characteristics of member countries, the financial markets exhibit a more complex interdependence. Therefore, it is necessary to consider risk factors and their dependence structures, delineate the relationships, identify risk spillover and contagion paths between financial markets, and predict potential financial turbulence in the future.

The dependent structure of financial markets has consistently been a focal point in academic research. Financial dependence refers to the mutually supportive relationships between financial markets, commonly used to describe the connections between prices or returns in financial markets. Forbes [1] posited that the underlying cause of correlation in financial markets is fundamentally rooted in cross-market transmission triggered by informational shocks. The volatility in a specific market can lead to changes of other markets, and interdependence can capture the trends and degree of such changes among different markets. Dependence structure refers to the functional relationship of mutual dependence between variables; it serves as a quantitative form of measuring the interdependence in financial markets [2]. Stock market interdependence captures these changing trends and degrees of correlation between different markets. Currently, the main methods for studying the interdependence structure among financial markets include linear correlation analysis, Granger causality testing, Cointegration analysis, time series models, GARCH family models, and Copula models.

In the early stages, correlation tests utilized the linear correlation coefficient method to analyze the interdependence of return sequences at the mean level. However, this approach could not accurately capture the nonlinear characteristics often present in real financial data. Granger causality testing and cointegration analysis offer a better description of the linear relationships between variables. Alagidede et al. [3] employed Granger causality tests to study the causal relationships between exchange rates and stock prices in Canada, Switzerland, and the UK, revealing the existence of causal links between stock and foreign exchange markets. Khan et al. [4] conducted cointegration tests on the stock and foreign exchange markets in India. When modeling market relationships using Granger causality analysis, cointegration tests, it is assumed that the joint distribution and marginal distributions of market returns follow a normal distribution. However, The GARCH model is unable to capture nonlinear structures and explain negative correlations between assets as well as asymmetrical phenomena in capital markets. The EGARCH model can capture asymmetric distributions. Currently, scholars widely employ the EGARCH model to describe the autoregressive, heteroscedastic, and leverage effects in financial markets. Kanas [5] used the EGARCH model to analyze volatility spillover effects between stock returns and exchange rate in six countries. Yang and Doong [6] using the EGARCH model to examine volatility spillover relationships between stock markets and foreign exchange markets in G7 countries. Ba et al. [7], used the EGARCH model to analyze the spillover relationship between stock prices and exchange rates in China. They discovered that the volatility spillover effect from the stock market to the foreign exchange market is asymmetric.Utilizing the EGARCH model to determine the marginal distribution of variables allows for obtaining the standardized residual sequence for the joint distribution.

Sklar [8] introduced Copula functions, which connects the joint distribution of variables with their respective marginal distributions to characterize the non-linear tail dependence structure in financial markets. The fundamental idea of Copula is to transform marginal variables into uniform distribution variables, defining correlation as a joint distribution over the uniform distribution. Copula functions have a clear advantage in depicting nonlinear and tail dependencies. They allow each variable to follow different distribution assumptions and are not constrained by marginal distribution limitations. Scholars turned to Copula to depict the dependency relationships and risk spillover effects between variables [9–11]. But Gaussian Copula is symmetric, and it cannot reflect tail features. Archimedes Copula assumes



that the dependence structure between any two variables is the same, which does not happen in reality.To describe the correlations between multiple variables, Joe [12] proposed constructing the joint distribution of multivariate variables using Pair Copula functions. Bedford and Cooke [13] introduced Vine Copula to illustrate the structure of Pair Copula decomposition. The Vine Copula, accurately depicts the dependency relationships between variables through a tree structure. At present, dependency analysis has been widely used in the analysis of financial markets, investment portfolios and financial risks, as well as in the research of financial issues such as asset pricing and asset allocation [14–17].

This study utilizes the ARMA-EGARCH-Vine-Copula approach to analyze the dependence structure of stock markets among RCEP countries.Firstly, the ARMA-EGARCH model was used to filter the time series data of stock indices. The ARMA model eliminates autocorrelation in the original sequence, while the EGARCH model removes heteroscedasticity. This process yields standardized residuals, obtained the marginal distributions of each variable. Finally, we used Vine-Copula to characterize the dependence structure among the stock markets.

2. DATA AND DATA PROCESSING

2.1. Data

This article selects the stock market indices of member countries within the RCEP (Regional Comprehensive Economic Partnership) that can represent the overall performance of the stock market. Considering data availability, Brunei, Laos, Myanmar, and Cambodia have relatively lower total foreign trade volumes and weaker financial market development compared to other countries. Therefore, this paper focuses on 11 countries for analysis; These were, China, Thailand, Singapore, Malaysia, Japan, South Korea, New Zealand, Australia, the Philippines, Indonesia, and Vietnam, to study the dependent structure of these countries' stock markets before and after the implementation of the RCEP. Stock index data was downloaded from website https://cn.investing.com/.

We collected daily trading index data for each country spanning the period from January 1, 2019, to November 21, 2023. The dataset included indices of China (CSI 1000), Thailand (SET), Singapore (STI), Malaysia (KLSE), Japan (TOPX1000), Korea (KOSPI50), New Zealand (NZMC), Australia (ASX200), Philippines (PSI), Indonesia (JCI), and Vietnam (VN30).

2.2. Data Processing

After excluding data mismatched with holidays and non-matching trading hours across different countries due to variations in holidays and market operating hours, a total of 1184 sample sets were obtained. To investigate the impact of RCEP, the whole sample was divided into two sub-samples: sub-sample 1, representing the period before the implementation of the RCEP framework (from January 1, 2019, to January 1, 2022), with a sample size of 735; sub-sample 2, covering the period from the implementation of the RCEP framework until the present (from January 1, 2022, to November 21, 2023), with a sample size of 524. The time series of stock indices for each country are illustrated in Fig. 1.

The stock market indices for various countries were transformed into return sequences by using the logarithmic return formula $r(t) = \ln P(t) + \ln P(t-1)$, P_t is the closed price on day. This transformation results in logarithmic return sequences.

From Fig. 2, it is observed that the daily logarithmic return sequences exhibited significant volatility and concentration, displaying clustering of volatility. Extreme values were concentrated within specific time intervals. Descriptive statistics were applied to the return sequences, including mean, standard deviation, skewness, and kurtosis.

From Table 1, it can be observed that, except for Singapore, the return sequences of stock indices for all countries exhibit left-skewness, with kurtosis exceeding 3. This indicates that the log return sequences display sharp peak and left-skewness characteristics. We used ADF (Augmented Dickey-Fuller) test, Jarque–Bera test, Ljung–Box test to check stationary and independence of time series data. The Jarque–Bera test was used to judge whether the sample data conformed to the normal distribution. If the value was significantly greater than 0, it indicates that the sample data did not follow a normal distribution. The ADF test is used to analyze the stationary of logarithmic return series of stock index. Alternative hypothesis is stationary. The Ljung–Box test can determine whether the sequence is purely

Table 1. The descriptive statistics of stock market index for each countries

Countries	Mean	SD	Skewness	Kurtosis
China	2.900	0.014	−0.709	6.403
Thailand	−0.805	0.011	−2.004	27.927
Malaysia	−1.106	0.008	−0.088	11.969
Japan	4.019	0.011	−0.047	6.540
Korea	1.878	0.012	−0.141	10.113
Singapore	0.158	0.009	0.371	25.171
New Zealand	−0.336	0.009	−2.949	49.851
Australia	2.042	0.011	−1.198	16.818
Philippines	−1.584	0.014	−1.517	18.755
Indonesia	1.004	0.010	−0.214	15.279
Vietnam	2.187	0.014	−1.123	9.491

Table 2. The result of JB ADF Ljung−Box tests

Countries	JB	ADF	$Ljung--BoxQ$
China	670.62***	−9.957***	11.966
Thailand	31447.0***	−8.688***	51.115***
Malaysia	3970.4***	−10.079***	20.7**
Japan	618.68***	−10.467***	10.257
Korea	2499.8***	−10.075***	26.292***
Singapore	24277.0***	−9.180***	57.172***
New Zealand	110004.0***	−9.553***	48.963***
Australia	9702.7.0***	−8.426***	91.307***
Philippines	12700.0***	−10.036***	19.562**
Indonesia	7447.2***	−10.892***	21.198***
Vietnam	2326.9***	−9.570***	9.667

* ***, **, * Significant at 1%, 5% and 10% levels.

3. METHODOLOGY

This study employed the ARMA-EGARCH-Vine-Copula approach to investigate the dependence structure among stock markets of RCEP countries. Firstly, the time series data of stock indices were filtered to eliminate characteristics such as autocorrelation and volatility clustering in the original sequences. This process results in standardized residuals that approximate independent and identical distribution. Secondly, the marginal distributions for each sample are determined, allowing for the probability integral transformation of residuals into sequences following a uniform distribution. Finally, an appropriate Vine-Copula function was selected to characterize the dependence structure among the stock markets.

3.1. Time-Series Analysis

Extensive empirical analyses of stock market return series indicated characteristics of sharp peak and heavy tail, and the clustering phenomenon of volatility, namely the aggregation of extremes.

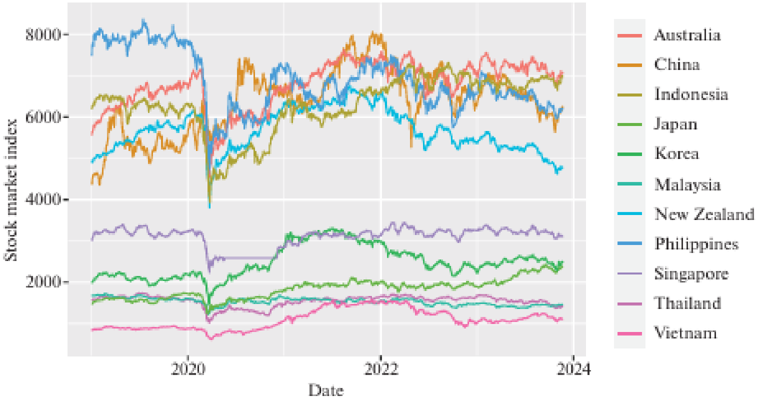


Fig. 1. Time series data of stock market index.

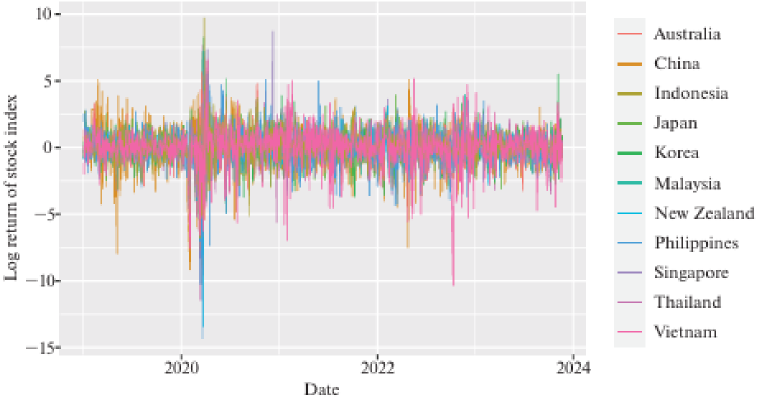


Fig. 2. Log return data of stock market index.

random, and avoid auto-correlation affecting the accuracy of the time series model. If the observed values are not mutually independent, then the observations may be correlated with another observation after a certain period of time, the time series data has ARCH effect.

From the results shown in Table 2, it can be observed that the JB statistic was significantly larger than 0 for all sequences, indicating rejection of the normality assumption. The p-values of the ADF test indicate significant rejection of the null hypothesis, suggesting the sequences is stationary. The Ljung–Box Q (10) test is for the ARCH effect with a lag of 10 periods. Except for China, Japan, and Vietnam, the stock market log returns exhibited autocorrelation, and significant ARCH effects were observed. Through the aforementioned data processing steps, the original time series data of stock indices were transformed into stationary return series.

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Japan	4.019	0.011	−0.047	6.540
Korea	1.878	0.012	−0.141	10.113
Singapore	0.158	0.009	0.371	25.171
New Zealand	−0.336	0.009	−2.949	49.851
Australia	2.042	0.011	−1.198	16.818
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* ***, **, * Significant at 1%, 5% and 10% levels.

3. METHODOLOGY

This study employed the ARMA-EGARCH-Vine-Copula approach to investigate the dependence structure among stock markets of RCEP countries. Firstly, the time series data of stock indices were filtered to eliminate characteristics such as autocorrelation and volatility clustering in the original sequences. This process results in standardized residuals that approximate independent and identical distribution. Secondly, the marginal distributions for each sample are determined, allowing for the probability integral transformation of residuals into sequences following a uniform distribution. Finally, an appropriate Vine-Copula function was selected to characterize the dependence structure among the stock markets.

3.1. Time-Series Analysis

Extensive empirical analyses of stock market return series indicated characteristics of sharp peak and heavy tail, and the clustering phenomenon of volatility, namely the aggregation of extremes.

Actual stock return rate sequences often exhibit autocorrelation and heteroscedasticity. Prior to constructing a Copula model, it is necessary for the distribution of financial time series to be at least asymptotically independent and identically distributed. Hence, time series data needs to be filtered to eliminate temporal dependencies such as autocorrelation and volatility clustering. ARMA models can correct for autocorrelation in time series, while GARCH models can correct for autoregressive conditional heteroscedasticity. Following the selection of ARMA-GARCH model orders based on the AIC (Akaike information criterion), model parameters were estimated by maximum likelihood to obtain standardized residual sequences after model filtering. Subsequently, marginal distributions for each sample were determined, yielding probability integral transformation residual sequences conforming to the $[0, 1]$ uniform distribution. Finally, an appropriate Copula function was selected to characterize the interdependence structure in the stock market.

The ARMA (AutoRegressive Moving Average) model is a method used to describe time series, combining both AutoRegressive (AR) and Moving Average (MA) processes. The orders, denoted as p and q, in an $ARMA(p, q)$ model represent the orders of the autoregressive and moving average components, respectively. The parameters of the ARMA model are estimated using the Maximum Likelihood Estimation method. The mathematical representation of the $ARMA(p, q)$ model is as follows

$$X(t) = \phi_0 + \sum_{i=1}^{p} \phi_i X_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}.$$

When fitting a time series, it is recommended to start with lower-order models, aiming for smaller values of p and q. During the order selection process, one should consider the AIC and opt for the order with the lowest AIC value. Following this, the model parameters are estimated using the Maximum Likelihood Estimation method. After the model is fitted, it is crucial to perform a white noise test on the residual sequence to ensure the model adequately captures the data. Through the fitting of logarithmic return series data for stock indices across different countries, we determine the optimal values for p and q.

3.2. GARCH Model

In 1982, R.F. Engle introduced the ARCH model (AutoRegressive Conditionally Heteroscedastic model) [18], which accurately captures the characteristics of financial time series and represents the changing volatility over time as a statistical model. The core idea of the ARCH model is that volatility is conditionally heteroskedastic, meaning that the size of volatility depends on past levels of volatility. The form of the model can be expressed as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2,$$

where σ_t^2 is the volatility at time t, ε_{t-i} is the residual at time $t - i$ (the difference between observed and predicted values), and α_0 and α_i are the model parameters that control the impact of past residuals.

Bollerslev extended the ARCH model and introduced the GARCH (Generalized AutoRegressive Conditional Heteroscedasticity model) [19]. This expansion incorporated the concept of past volatility, enhancing the model's flexibility to better describe logarithmic returns and comprehensively capture long-term financial data volatility trends. The GARCH model can be expressed as

$$\begin{cases} \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-i}^2, \\ a_t = \sigma_t \varepsilon_t. \end{cases}$$

However, the GARCH model struggles to measure the asymmetry of return volatility and the leverage effect in financial assets. In 1991, Bollerslev proposed the EGARCH model to address the issue of symmetric treatment of volatility shocks. The EGARCH model permits volatility to react differently to positive and negative news shocks, allowing for a more accurate capture of asymmetric volatility in financial time series. The expression for the EGARCH model is as follows

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i (\varepsilon_{t-i} - \gamma_i \varepsilon_{t-i}) + \sum_{j=1}^{q} \beta_j \log \sigma_{t-i}^2,$$

where σ_t^2 is the volatility at time t, ε_{t-i} is the residual at time $t-i$, and ω is the constant.

In this article, the $ARMA(p,q)-EGARCH(1,1)$ model was established to model the marginal distribution of the log return series of RECP countries, and the boundary density of the corresponding variable was obtained. The autocorrelation test and heteroscedasticity test are carried out on the obtained residual sequence. The standard residual sequence of each rate of return was obtained

$$\begin{cases} X(t) = \mu + \sum_{i=1}^{p} AR_i X_{t-i} + \sum_{i=1}^{q} MA_j \varepsilon_{t-j} + \varepsilon_t, \\ \varepsilon_t = z_t \sigma_t, \\ \ln \sigma_t^2 = \omega + \beta \ln \sigma_{t-1}^2 + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} - \sqrt{\frac{2}{\pi}} \right], \end{cases}$$

where X is the log return, μ is the drift term, ε is the error term, γ captures the size effect, and z is the standardized residual with skewed Student-t distribution.

Through maximizing the likelihood estimation of parameters in the ARMA-EGARCH model, distinct models for the stock indices in 11 countries are derived. From the equation above, AR and MA correspond to parameters within the ARMA model, while μ, α, ω, β, and γ are associated with parameters can calculate within EGARCH model. Additionally, skew and shape refer to parameters in the skewed t-distribution, with LLH indicating the log-likelihood. Using this model to filter the variables, we can retrieve the standard residual sequence.

3.3. Copula

The word "Copula" derives from the Latin verb "Copulare" and means to "bond" or "tie". Copula is a model used to describe the dependence relationship between random variables. The Copula approach was introduced by Sklar (1959). In the mid-1990s Copula were used as a tool for modeling dependencies between assets in empirical finance.

Let X be a d-dimensional continuous random vector with joint distribution function F, marginal distribution functions F_j, and marginal density functions f_j for $j = 1, \ldots, d$. Then, the joint distribution function can be expressed as

$$F(x_1, \ldots, x_d) = C(F_1(x_1), \ldots, F_d(x_d)),$$

with associated density $f(x_1, \ldots x_d) = c(F_1(x-1), \ldots, F_d(x_d)) f_1(x_1) \ldots f_d(x_d)$ for d dimensional copula C with Copula density c.

Using this theorem, flexible multivariate distributions can be constructed from d-dimensional copulas. Joe [12] initially introduced Pair-Copula Constructions (PCC) functions to construct joint distributions for multivariate variables.

For $d = 2$, we can immediately derive expressions for the conditional density and distribution functions, which are needed later. The conditional density $f_{1|2}$ and distribution function $F_{1|2}$ can be expressed as:

$$f_{1|2}(x_1|x_2) = c_{12}(F_1(x_1), F_2(x_2)) f_2(x_2),$$

$$F_{1|2}(x_1|x_2) = \frac{\partial}{\partial F_2(x_2)} C_{12}(F_1(x_1), F_2(x_2)) = \frac{\partial}{\partial \nu} C_{12}(F_1(x_1), \nu)|_{\nu = F_2(x_2)}.$$

Base on Joe's research, Bedford and Cooke (2001) summarized the formula of general d-dimensional Vine-Copula, proposed the Regular Vine-Copula model to characterize the structure of Pair Copula decomposition [13].

Vine Copula is a graphical structure used to build the dependency structure between multivariate distributions. It takes the form of a tree structure, where each node represents a bivariate Copula, and the entire structure forms a tree.

A vine structure with d dimensional variables is composed of $d-1$ tree $(T_1, T_2, \ldots, T_d)$ and every tree is composed of many nodes and edges for which the relationships below are satisfied: (1) For T_i $(i = 1, 2, \ldots, d-1)$, there are $d-i$ edges in E_i, with $d-i+1$ nodes in N_i; (2) two nodes in tree $i+1$ are only connected by an edge if these nodes share a common node in tree i. Every edge $e = j(e), k(e)|D(e)$ in E_i can be used to represent a Pair Copula function $C_{j(e),k(e)|D(e)}$, where $j(e), k(e)$

Table 3. The estimator of ARMA model for each country

Countries	p	q	AR1	AR2	AR3	AR4	AR5	MA1	MA2	MA3	MA4
China	1	0	0.032								
Thailand	5	5	−0.747	−0.282	−0.273	−0.732	−0.977	0.751	0.291	0.285	0.744
Malaysia	2	5	0.436	−0.973				−0.513	1.067	−0.093	0.046
Japan	4	4	0.369	−0.340	0.339	0.614		−0.394	0.365	−0.381	−0.610
Korea	5	3	−0.142	−0.196	−0.923	0.016	0.055	0.151	0.247	0.971	
Singapore	5	4	0.775	0.187	0.457	−0.604	−0.032	−0.789	−0.205	−0.429	0.632
New Zealand	5	3	0.875	0.470	−0.874	−0.083	0.117	−0.875	−0.382	0.832	
Australia	5	4	0.628	−0.557	−0.392	0.335	−0.031	−0.675	0.584	0.328	−0.293
Philippines	4	4	0.127	0.502	0.394	−0.813		−0.178	−0.549	−0.394	0.851
Indonesia	5	5	0.065	−0.349	0.090	0.453	−0.385	−0.146	0.306	−0.069	−0.430
Vietnam	1	0	0.001								

is called conditioned nodes while $D(e)$ is conditioning sets.The right part of the representation above is R-vine Copula, which is composed of $d(d-1)/2$ Pair Copula:

$$f(x_1, x_2, \ldots, x_d) = \left[\prod_{k=1}^{d} f_k(x_k)\right] \left[\prod_{i=1}^{d-1} \prod_{e \in E_i} c_{j(e),k(e)|D(e)} \left(F\left(x_{j(e)} \mid \mathbf{x}_{D(e)}\right), F\left(x_{k(e)} \mid \mathbf{x}_{D(e)}\right)\right)\right],$$

where $X_{D(e)}$ represents a subset of $X = (x_1, x_2, \ldots, x_d)'$ represents a subset of $D(e)$.

Vine Copula consist of a sequence of nested trees that describe the Pair Copula functions unconditionally in the first tree and conditionally for the rest of the trees. Dissmann et al. (2013) introduced an automated algorithm including finding out an optimal R-vine tree structure, the Pair Copula families, and the parameter values of each best Pair Copula families based on AIC [20]. Firstly, the strongest dependence relationship between variables is captured, the degree of dependence between two nodes in the first layer tree is measured by the rank correlation coefficient τ, and the Pair copula is estimated between the selected variables. The form of rank correlation coefficient τ is

$$\tau(X,Y) = 4\int_0^1\int_0^1 C(u_1,u_2)dC((u_1,u_2) - 1,$$

the formula of Pair Copula function used in this paper is shown in Table 5.

In this paper, we modeled the marginal distribution of the return sequences of the RCEP countries based on the ARMA(p,q)-EGARCH(1,1) model, so the corresponding marginal density of variables was obtained. Autocorrelation tests and heteroskedasticity tests were conducted on the resulting residual sequences to obtain standardized, independently and identically distributed residual sequences. After transforming the fitted standardized residuals, making them follow a uniform distribution, the R-Vine-Copula method was applied to model the sequences.

3.4. Accuracy Model

AIC (Akaike information criterion) was used as an indicator to measure the performance of various marginal distributions and the best fitted Copula model. The criterion for selecting the appropriate Copula function by AIC is that the smaller the AIC value, the better the fitting effect

$$AIC = -2\sum_{i=1}^{n} \log f(x_i|\hat{\theta}) + 2k.$$

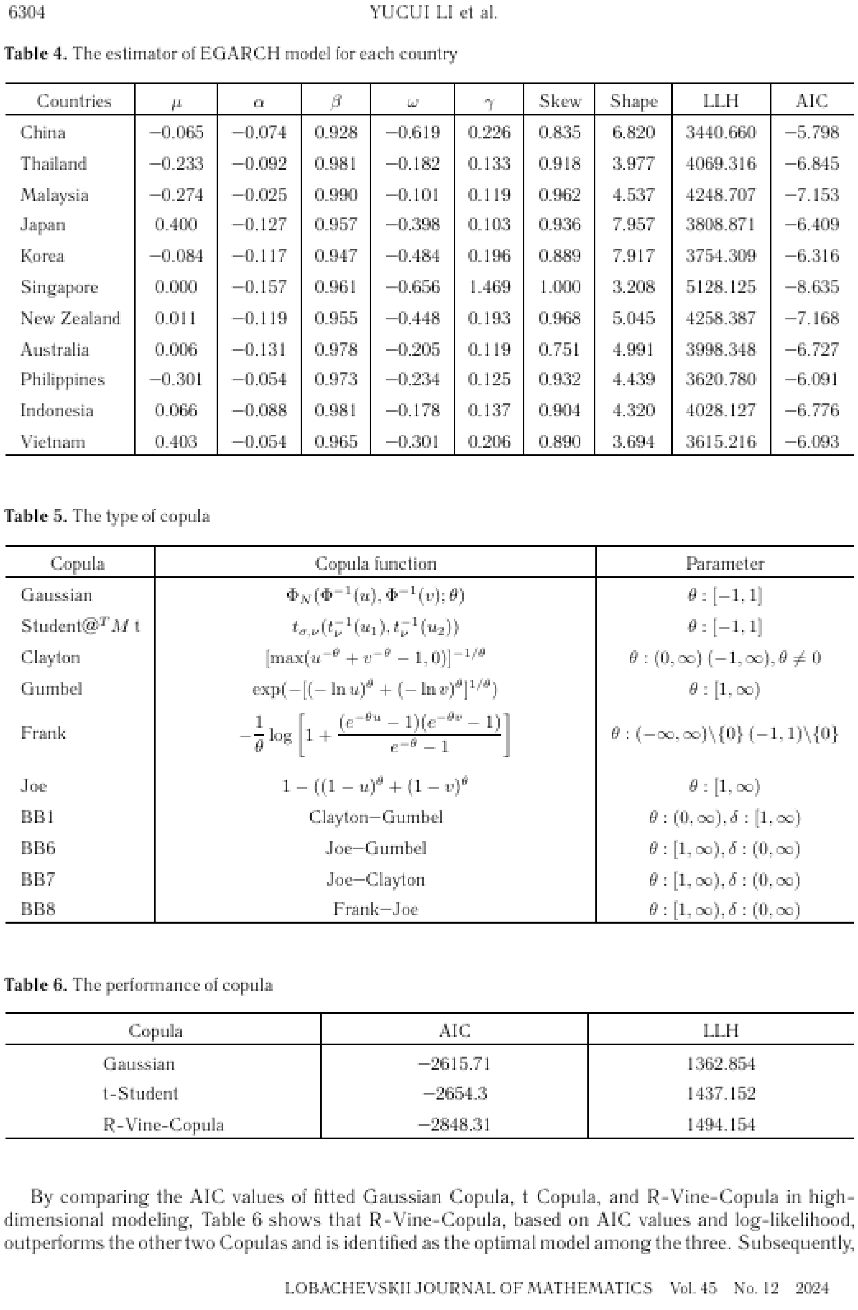

Table 4. The estimator of EGARCH model for each country

Countries	μ	α	β	ω	γ	Skew	Shape	LLH	AIC
China	−0.065	−0.074	0.928	−0.619	0.226	0.835	6.820	3440.660	−5.798
Thailand	−0.233	−0.092	0.981	−0.182	0.133	0.918	3.977	4069.316	−6.845
Malaysia	−0.274	−0.025	0.990	−0.101	0.119	0.962	4.537	4248.707	−7.153
Japan	0.400	−0.127	0.957	−0.398	0.103	0.936	7.957	3808.871	−6.409
Korea	−0.084	−0.117	0.947	−0.484	0.196	0.889	7.917	3754.309	−6.316
Singapore	0.000	−0.157	0.961	−0.656	1.469	1.000	3.208	5128.125	−8.635
New Zealand	0.011	−0.119	0.955	−0.448	0.193	0.968	5.045	4258.387	−7.168
Australia	0.006	−0.131	0.978	−0.205	0.119	0.751	4.991	3998.348	−6.727
Philippines	−0.301	−0.054	0.973	−0.234	0.125	0.932	4.439	3620.780	−6.091
Indonesia	0.066	−0.088	0.981	−0.178	0.137	0.904	4.320	4028.127	−6.776
Vietnam	0.403	−0.054	0.965	−0.301	0.206	0.890	3.694	3615.216	−6.093

Table 5. The type of copula

Copula	Copula function	Parameter
Gaussian	$\Phi_N(\Phi^{-1}(u), \Phi^{-1}(v); \theta)$	$\theta : [-1, 1]$
Student@$^T M$ t	$t_{\sigma,\nu}(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2))$	$\theta : [-1, 1]$
Clayton	$[\max(u^{-\theta} + v^{-\theta} - 1, 0)]^{-1/\theta}$	$\theta : (0, \infty)\ (-1, \infty), \theta \neq 0$
Gumbel	$\exp(-[(-\ln u)^\theta + (-\ln v)^\theta]^{1/\theta})$	$\theta : [1, \infty)$
Frank	$-\frac{1}{\theta} \log \left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}\right]$	$\theta : (-\infty, \infty) \backslash \{0\}\ (-1, 1) \backslash \{0\}$
Joe	$1 - ((1 - u)^\theta + (1 - v)^\theta$	$\theta : [1, \infty)$
BB1	Clayton−Gumbel	$\theta : (0, \infty), \delta : [1, \infty)$
BB6	Joe−Gumbel	$\theta : [1, \infty), \delta : (0, \infty)$
BB7	Joe−Clayton	$\theta : [1, \infty), \delta : (0, \infty)$
BB8	Frank−Joe	$\theta : [1, \infty), \delta : (0, \infty)$

Table 6. The performance of copula

Copula	AIC	LLH
Gaussian	−2615.71	1362.854
t-Student	−2654.3	1437.152
R-Vine-Copula	−2848.31	1494.154

By comparing the AIC values of fitted Gaussian Copula, t Copula, and R-Vine-Copula in high-dimensional modeling, Table 6 shows that R-Vine-Copula, based on AIC values and log-likelihood, outperforms the other two Copulas and is identified as the optimal model among the three. Subsequently,

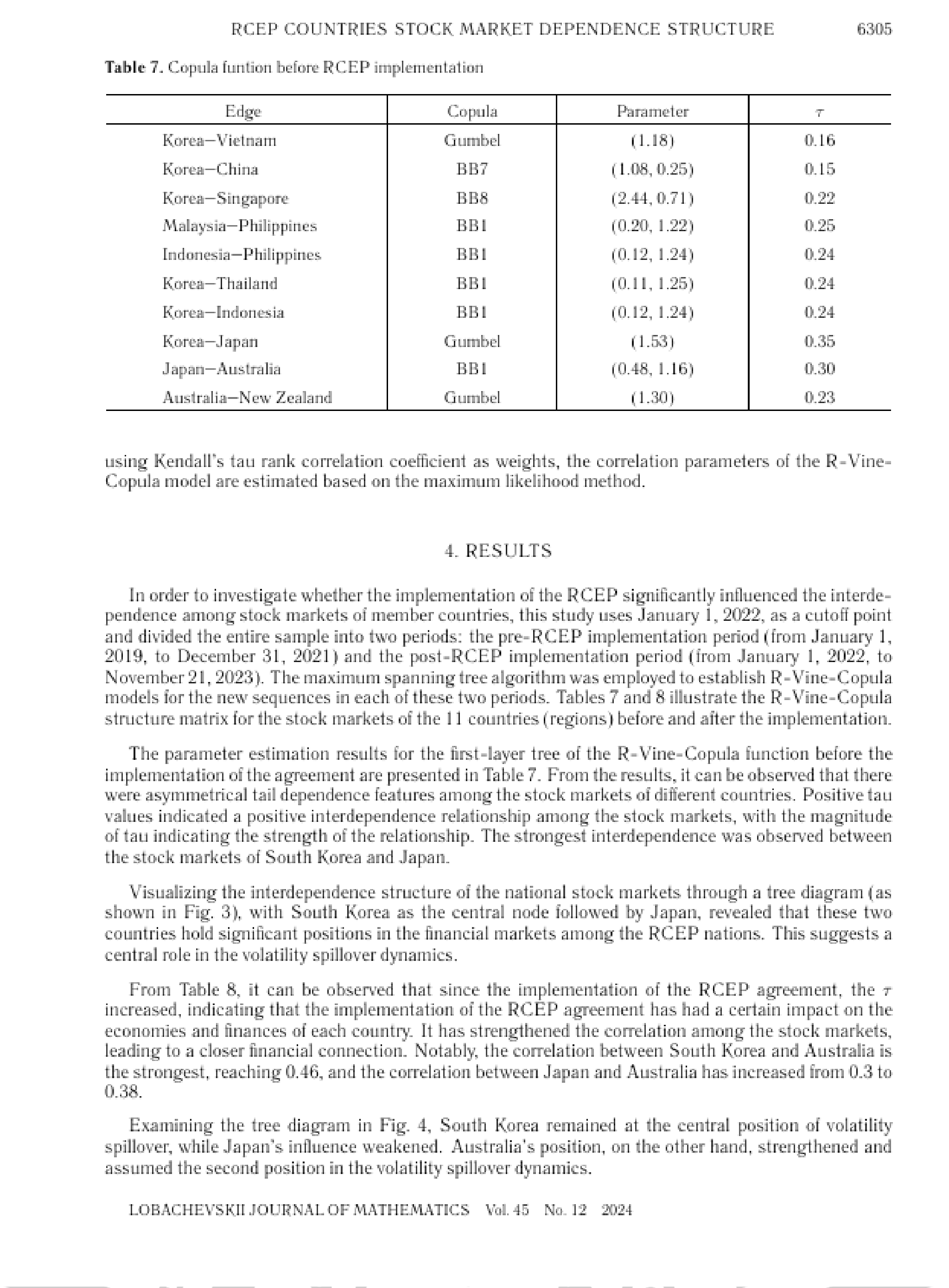

Table 7. Copula funtion before RCEP implementation

Edge	Copula	Parameter	τ
Korea–Vietnam	Gumbel	(1.18)	0.16
Korea–China	BB7	(1.08, 0.25)	0.15
Korea–Singapore	BB8	(2.44, 0.71)	0.22
Malaysia–Philippines	BB1	(0.20, 1.22)	0.25
Indonesia–Philippines	BB1	(0.12, 1.24)	0.24
Korea–Thailand	BB1	(0.11, 1.25)	0.24
Korea–Indonesia	BB1	(0.12, 1.24)	0.24
Korea–Japan	Gumbel	(1.53)	0.35
Japan–Australia	BB1	(0.48, 1.16)	0.30
Australia–New Zealand	Gumbel	(1.30)	0.23

using Kendall's tau rank correlation coefficient as weights, the correlation parameters of the R-Vine-Copula model are estimated based on the maximum likelihood method.

4. RESULTS

In order to investigate whether the implementation of the RCEP significantly influenced the interdependence among stock markets of member countries, this study uses January 1, 2022, as a cutoff point and divided the entire sample into two periods: the pre-RCEP implementation period (from January 1, 2019, to December 31, 2021) and the post-RCEP implementation period (from January 1, 2022, to November 21, 2023). The maximum spanning tree algorithm was employed to establish R-Vine-Copula models for the new sequences in each of these two periods. Tables 7 and 8 illustrate the R-Vine-Copula structure matrix for the stock markets of the 11 countries (regions) before and after the implementation.

The parameter estimation results for the first-layer tree of the R-Vine-Copula function before the implementation of the agreement are presented in Table 7. From the results, it can be observed that there were asymmetrical tail dependence features among the stock markets of different countries. Positive tau values indicated a positive interdependence relationship among the stock markets, with the magnitude of tau indicating the strength of the relationship. The strongest interdependence was observed between the stock markets of South Korea and Japan.

Visualizing the interdependence structure of the national stock markets through a tree diagram (as shown in Fig. 3), with South Korea as the central node followed by Japan, revealed that these two countries hold significant positions in the financial markets among the RCEP nations. This suggests a central role in the volatility spillover dynamics.

From Table 8, it can be observed that since the implementation of the RCEP agreement, the τ increased, indicating that the implementation of the RCEP agreement has had a certain impact on the economies and finances of each country. It has strengthened the correlation among the stock markets, leading to a closer financial connection. Notably, the correlation between South Korea and Australia is the strongest, reaching 0.46, and the correlation between Japan and Australia has increased from 0.3 to 0.38.

Examining the tree diagram in Fig. 4, South Korea remained at the central position of volatility spillover, while Japan's influence weakened. Australia's position, on the other hand, strengthened and assumed the second position in the volatility spillover dynamics.

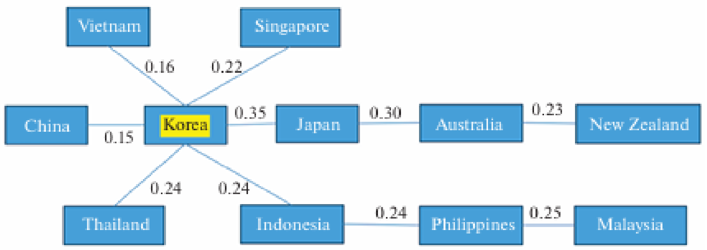

Fig. 3. The Vine Copula tree 1 before RCEP implementation.

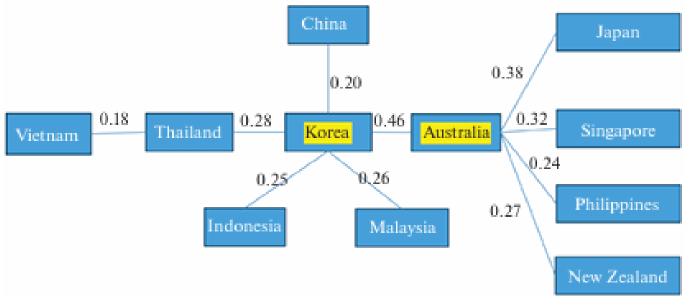

Fig. 4. The Vine Copula tree 1 after RCEP implementation.

5. DISCUSSION

The utilization of the ARMA-EGARCH model in this study to analyze marginal distributions of variables presents a robust approach. However, it is essential to acknowledge potential limitations arising from the uniform application of this model across all stock index return series. Future research endeavors could address this issue by exploring and comparing various GARCH models. Such an approach would enable the selection of the most appropriate GARCH model for each specific stock index return series, thereby enhancing the accuracy of marginal distribution estimation. Additionally, integrating extreme value theory into the analysis could offer further improvements in estimating marginal distributions, particularly in capturing tail behaviors more effectively.

Furthermore, while the Vine Copula model effectively captures the overall interdependence structure of stock markets, it is imperative to recognize the dynamic nature of financial markets. These markets are subject to continuous fluctuations, particularly in response to extreme events, which can significantly alter dependence structures. To address this challenge, future research could consider integrating dynamic Copula functions into the Vine Copula model. This approach, as proposed by Claudia Czado [17], would enable a more accurate depiction of the ever-evolving relationships among financial markets, thereby enhancing the model's predictive power and applicability in real-world scenarios.

6. CONCLUSIONS

In conclusion, the implementation of the RCEP agreement has led to enhanced economic ties among member nations and strengthened cooperation within the financial stock market domain, resulting in a more tightly interconnected structure among national stock markets. Through the utilization of an ARMA-EGARCH-Vine-Copula model, this study investigated the interdependence structure of stock markets across various RCEP countries.

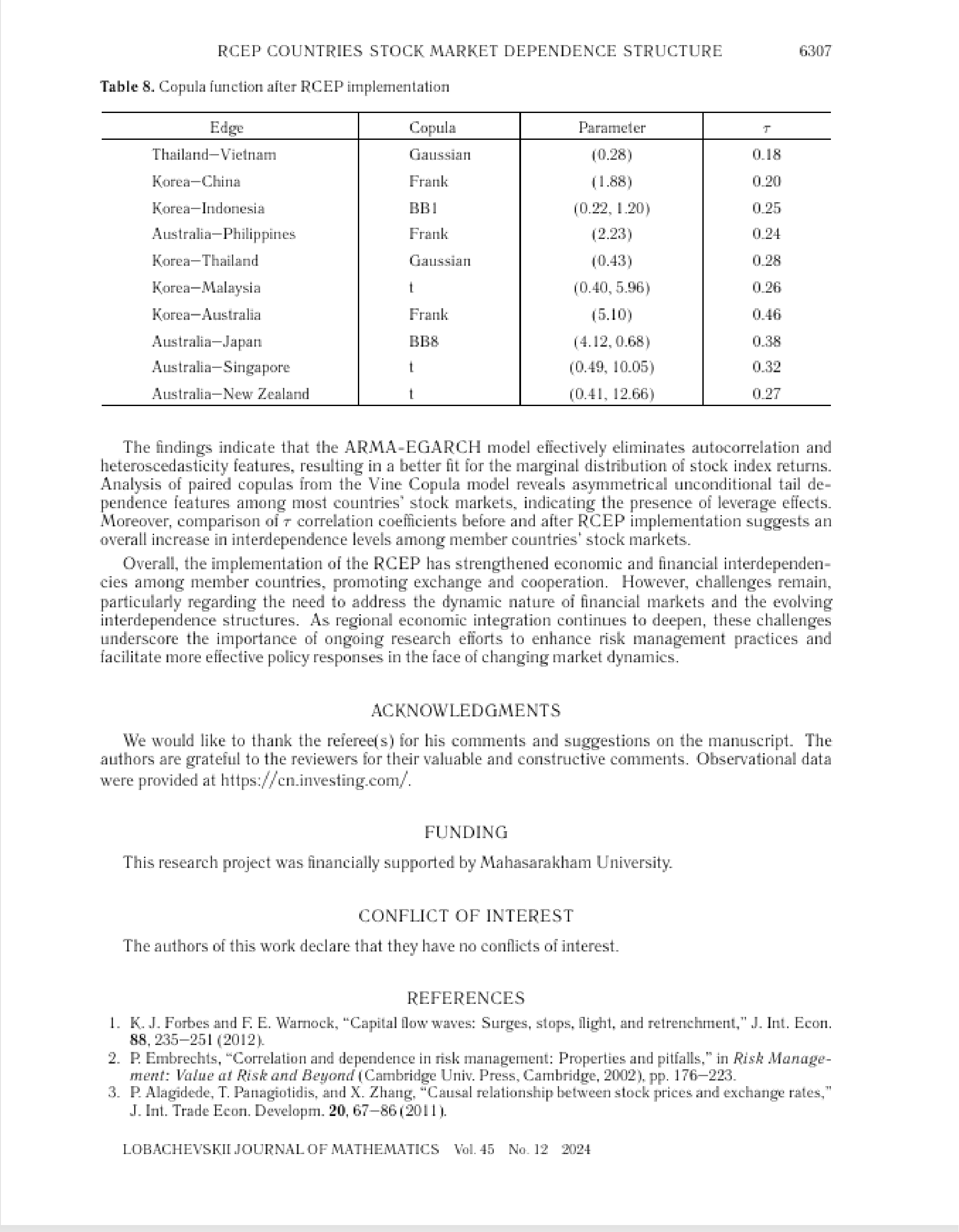

Table 8. Copula function after RCEP implementation

Edge	Copula	Parameter	τ
Thailand–Vietnam	Gaussian	(0.28)	0.18
Korea–China	Frank	(1.88)	0.20
Korea–Indonesia	BB1	(0.22, 1.20)	0.25
Australia–Philippines	Frank	(2.23)	0.24
Korea–Thailand	Gaussian	(0.43)	0.28
Korea–Malaysia	t	(0.40, 5.96)	0.26
Korea–Australia	Frank	(5.10)	0.46
Australia–Japan	BB8	(4.12, 0.68)	0.38
Australia–Singapore	t	(0.49, 10.05)	0.32
Australia–New Zealand	t	(0.41, 12.66)	0.27

The findings indicate that the ARMA-EGARCH model effectively eliminates autocorrelation and heteroscedasticity features, resulting in a better fit for the marginal distribution of stock index returns. Analysis of paired copulas from the Vine Copula model reveals asymmetrical unconditional tail dependence features among most countries' stock markets, indicating the presence of leverage effects. Moreover, comparison of τ correlation coefficients before and after RCEP implementation suggests an overall increase in interdependence levels among member countries' stock markets.

Overall, the implementation of the RCEP has strengthened economic and financial interdependencies among member countries, promoting exchange and cooperation. However, challenges remain, particularly regarding the need to address the dynamic nature of financial markets and the evolving interdependence structures. As regional economic integration continues to deepen, these challenges underscore the importance of ongoing research efforts to enhance risk management practices and facilitate more effective policy responses in the face of changing market dynamics.

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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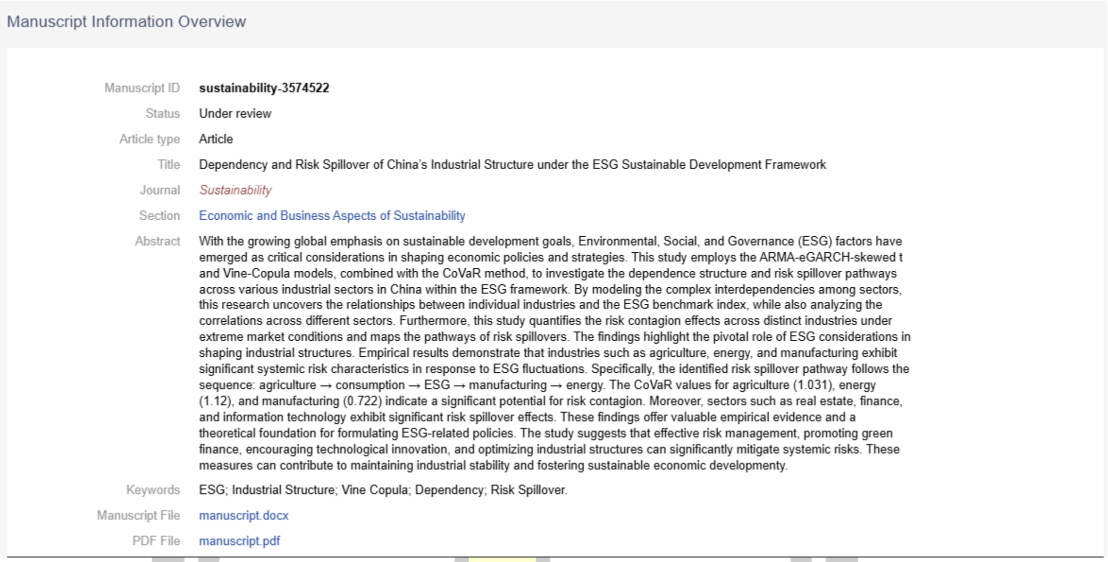
B.2 The 2^{nd} Manuscript



Manuscript Information Overview

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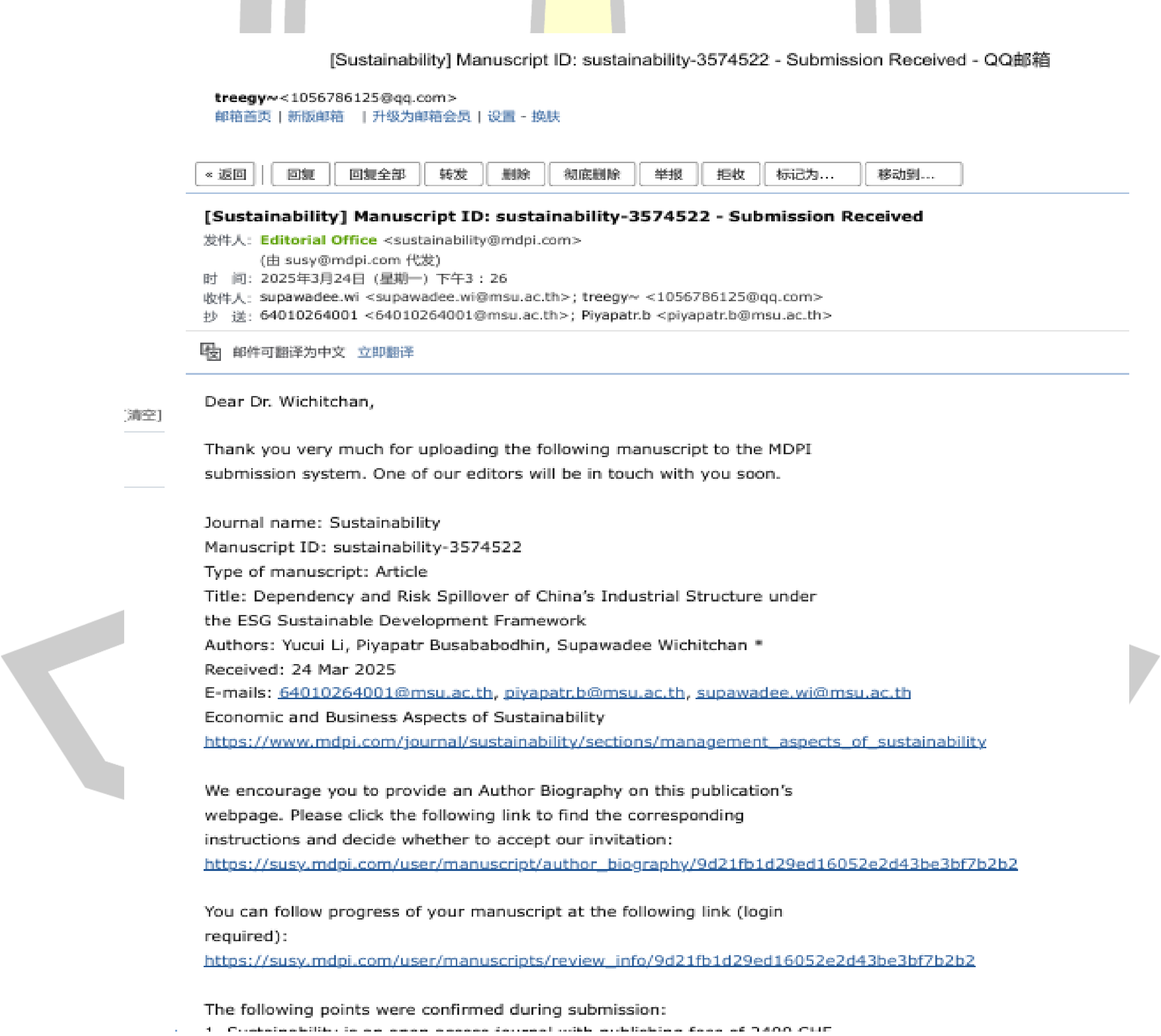
Status	Under review
Article type	Article
Title	Dependency and Risk Spillover of China's Industrial Structure under the ESG Sustainable Development Framework
Journal	*Sustainability*
Section	Economic and Business Aspects of Sustainability
Abstract	With the growing global emphasis on sustainable development goals, Environmental, Social, and Governance (ESG) factors have emerged as critical considerations in shaping economic policies and strategies. This study employs the ARMA-eGARCH-skewed t and Vine-Copula models, combined with the CoVaR method, to investigate the dependence structure and risk spillover pathways across various industrial sectors in China within the ESG framework. By modeling the complex interdependencies among sectors, this research uncovers the relationships between individual industries and the ESG benchmark index, while also analyzing the correlations across different sectors. Furthermore, this study quantifies the risk contagion effects across distinct industries under extreme market conditions and maps the pathways of risk spillovers. The findings highlight the pivotal role of ESG considerations in shaping industrial structures. Empirical results demonstrate that industries such as agriculture, energy, and manufacturing exhibit significant systemic risk characteristics in response to ESG fluctuations. Specifically, the identified risk spillover pathway follows the sequence: agriculture → consumption → ESG → manufacturing → energy. The CoVaR values for agriculture (1.031), energy (1.12), and manufacturing (0.722) indicate a significant potential for risk contagion. Moreover, sectors such as real estate, finance, and information technology exhibit significant risk spillover effects. These findings offer valuable empirical evidence and a theoretical foundation for formulating ESG-related policies. The study suggests that effective risk management, promoting green finance, encouraging technological innovation, and optimizing industrial structures can significantly mitigate systemic risks. These measures can contribute to maintaining industrial stability and fostering sustainable economic developmenty.
Keywords	ESG; Industrial Structure; Vine Copula; Dependency; Risk Spillover.
Manuscript File	manuscript.docx
PDF File	manuscript.pdf



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treegy~<1056786125@qq.com>

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抄　送：64010264001 <64010264001@msu.ac.th>; Piyapatr.b <piyapatr.b@msu.ac.th>

Dear Dr. Wichitchan,

Thank you very much for uploading the following manuscript to the MDPI submission system. One of our editors will be in touch with you soon.

Journal name: Sustainability
Manuscript ID: sustainability-3574522
Type of manuscript: Article
Title: Dependency and Risk Spillover of China's Industrial Structure under the ESG Sustainable Development Framework
Authors: Yucui Li, Piyapatr Busababodhin, Supawadee Wichitchan *
Received: 24 Mar 2025
E-mails: 64010264001@msu.ac.th, piyapatr.b@msu.ac.th, supawadee.wi@msu.ac.th
Economic and Business Aspects of Sustainability
https://www.mdpi.com/journal/sustainability/sections/management_aspects_of_sustainability

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The following points were confirmed during submission:

B.3 The 3rd Manuscript

Asymmetric Tail Dependence and Risk Spillovers in China's Agricultural Futures Market: A Vine Copula-ΔCoVaR Approach with Markov Regime Switching

Yucui Li, Lili Zhang,Supawadee Wichitchan,Piyapatr Busababodhin[c]

[a] *Business School, Guangxi Minzu Normal*
University, Chongzuo, 532200, Guangxi, China
[b] *College of Information and Communication, National University of Defense*
Technology, Wuhan, 430000, Hubei, China
[c] *Department of Mathematics, Faculty of Science, Mahasarakham*
University, Kantharawichai, 44150, Mahasarakham, Thailand

Abstract

Amid the high integration of global markets and frequent extreme events, China's agricultural futures market faces significant systemic risk challenges. This study constructs an analytical framework integrating the Vine Copula-ΔCoVaR method with a Markov regime-switching model, using exogenous factors such as extreme weather events (drought index), economic policy uncertainty (EPU), and market volatility index (VIX) to explore the asymmetric tail dependence structures and risk spillover paths between China's agricultural futures market and the crude oil, gold, exchange rates, domestic spot, and international agricultural product markets from a state-dependent perspective.

The markets are classified into three volatility states: low, high, and extreme. The empirical results show that in extreme volatility states, tail dependencies are highly asymmetric: the agricultural futures market exhibits strong negative dependence with the crude oil market in the lower tail, while it shows significant positive dependence with the gold market in the upper tail, reflecting risk escalation and hedging spillover effects. The Vine Copula modeling results further confirm that tail-focused copulas, such as Clayton, dominate the dependence structure in high volatility and extreme states, further emphasizing the nonlinear and asymmetric market interdependencies.

In terms of risk spillovers, ΔCoVaR results reveal clear asymmetric spillover

B.4 BioSat 2024 Conference

S-APS-O-005

CERTIFICATE

OF PARTICIPATION

1st International Conference on Biodiversity Science and Technology

(BiOSat2024)

This is to certify that

Li Yucui

has presented oral presentation entitled

" Dependence Structure and Extreme Risk Spillover in RCEP Countries: Constructing Copula Models from Time-Series Financial Market Data "

held on January 25 - 26, 2024. Pattaya, Thailand.
Organized under the collaborative efforts of Faculty of Technology, Faculty of Science,
and Walai Rukhavej Botanical Research Institute in Mahasarakham University.

Prof. Pairot Pramual, Ph.D.
Dean, Faculty of Science
Mahasarakham University

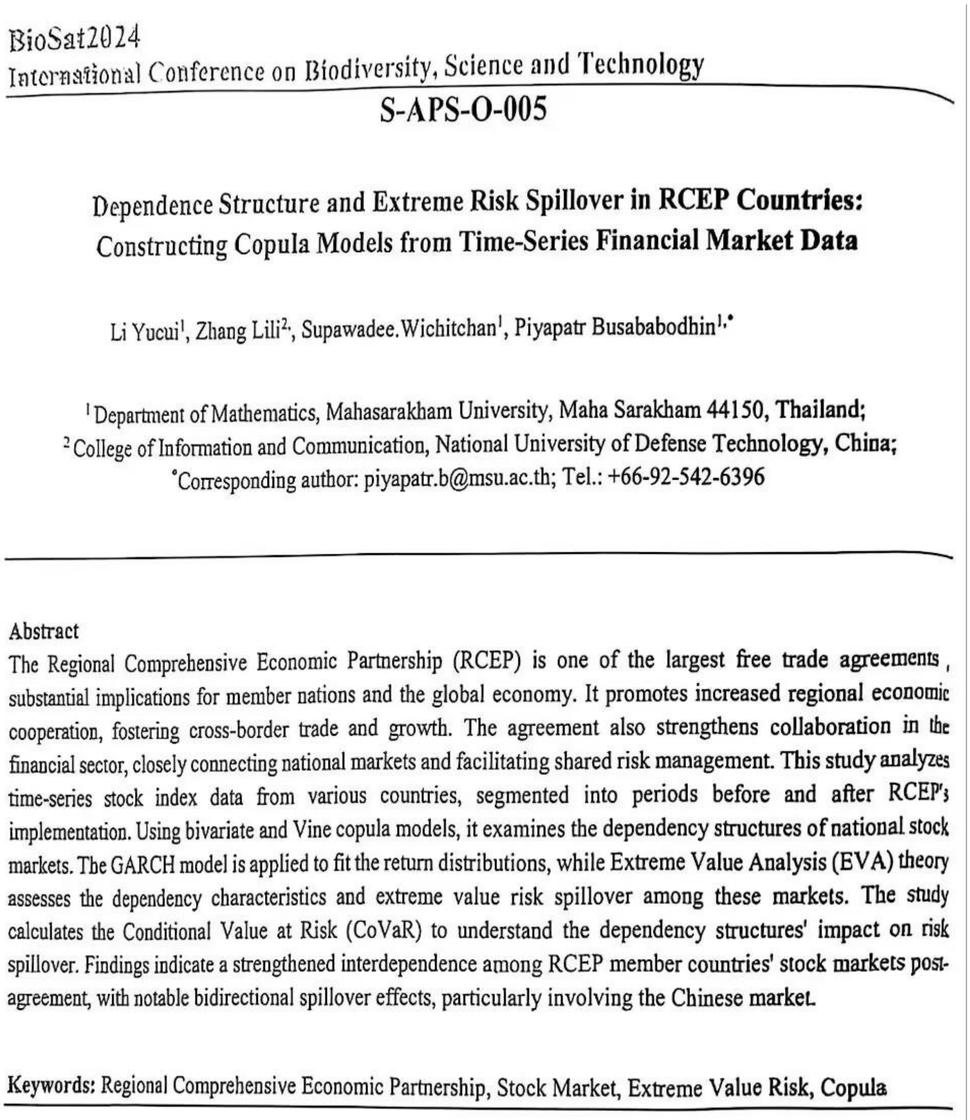
S. Thanonkeo
Asst.Prof. Sudarat Thanonkeo, Ph.D.
Director, Walai Rukhavej Botanical Research Institute
Mahasarakham University

Asst.Prof. Su[illegible]wan Chumchuere, Ph.D.
Dean, Faculty of Technology
Mahasarakham University

BioSat2024
International Conference on Biodiversity, Science and Technology

DAY 1: Thu 25th January 2024
Venue: D Varee Jomtien Beach, Pattaya, Chon Buri, Thailand.

	Meeting Room 2 - Applied Statistics (APS) Chair: *Assoc. Prof. Dr. Piyapatr Busababodhin*
10.30 – 10.45	S-APS-O-002_Identification of Earthquake Source Attributes Based on DAPSO-BP Combined Model Guoqing Chen
10.45 – 11.00	S-APS-O-003_Prioritization Matrix for Thailand i4.0 Index to Modernize Thai Industry Arnuphap Dowruen̲g
11.00 – 11.15	S-APS-O-004_ The Application of Genetic Algorithm Optimized Neural Network in Financial Risk Early Warning Model of Agricultural Listed Companies Song Yingying
11.15 – 11.30	S-APS-O-005_ Dependence Structure and Extreme Risk Spillover in RCEP Countries: Constructing Copula Models from Time-Series Financial Market Data Li Yucui
11.30 – 11.45	S-APS-O-006_ Enhancing Urban Community Governance in Southwest China: A Structural Equation Modeling Analysis of Key Factors in Guangxi Xiaona Zai
11.45 – 12.00	S-APS-O-007_Using Satellite Images and Statistics for Estimating Aboveground Forest Biomass Change in Dak Lak Province – Vietnam Ho Dinh Bao
	Meeting Room 3 - Biodiversity and local wisdom Chair: *Asst. Prof. Dr. Rachanee Nammatra*
10.30 – 10.45	B-BD-O-001_Erosion of Biodiversity Knowledge in the Utilization of Zingiberaceae Plants in Chon Buri Province, Thailand Thawatphong Boonma
10.45 – 11.00	B-BD-O-002 _Diversity and Ethnobotany of Commelinaceae in Lao PDR Anousone Sengthong
11.00 – 11.15	B-BD-O-003_Theropod Dinosaurs in Thailand: Implications for Paleobiogeography Kridsanupong Puntanon
11.15 – 11.30	B-BD-O-004_Preliminary Study of the Diversity of Aquatic Isopods in Mae Klong Estuary, Samut Songkhram Province Worradon Ngamboonkup
11.30 – 11.45	B-BD-O-005_Distribution and Conservation Status of Cyprinid Fishes in the Mekong Mainstream, Northeastern Thailand Saowapak Toemcheep
11.45 – 12.00	B-BD-O-006_Biodivesity, Traditional Knowledge, and Sustainable Use of Wild Mushrooms in the Northeastern of Thailand Khwanyuruan Naksuwankul



BioSat2024
International Conference on Biodiversity, Science and Technology

S-APS-O-005

Dependence Structure and Extreme Risk Spillover in RCEP Countries: Constructing Copula Models from Time-Series Financial Market Data

Li Yucui[1], Zhang Lili[2], Supawadee.Wichitchan[1], Piyapatr Busababodhin[1,*]

[1] Department of Mathematics, Mahasarakham University, Maha Sarakham 44150, Thailand;
[2] College of Information and Communication, National University of Defense Technology, China;
*Corresponding author: piyapatr.b@msu.ac.th; Tel.: +66-92-542-6396

Abstract

The Regional Comprehensive Economic Partnership (RCEP) is one of the largest free trade agreements , substantial implications for member nations and the global economy. It promotes increased regional economic cooperation, fostering cross-border trade and growth. The agreement also strengthens collaboration in the financial sector, closely connecting national markets and facilitating shared risk management. This study analyzes time-series stock index data from various countries, segmented into periods before and after RCEP's implementation. Using bivariate and Vine copula models, it examines the dependency structures of national stock markets. The GARCH model is applied to fit the return distributions, while Extreme Value Analysis (EVA) theory assesses the dependency characteristics and extreme value risk spillover among these markets. The study calculates the Conditional Value at Risk (CoVaR) to understand the dependency structures' impact on risk spillover. Findings indicate a strengthened interdependence among RCEP member countries' stock markets post-agreement, with notable bidirectional spillover effects, particularly involving the Chinese market.

Keywords: Regional Comprehensive Economic Partnership, Stock Market, Extreme Value Risk, Copula

B.5 ICAS 2024 Conference

ICAS

The 7th International Conference on Applied Statistics 2024 (ICAS2024)

this certificate is proudly presented to:

Yucui Li, Prapawan Chomphuwiset, Supawadee Wichitchan and Piyapatr Busababodhin

for presenting the paper entitled:

Dependency and Risk Spillover of China's Industrial Structure Under the ESG Sustainable Development Framework

October 24 - 25, 2024 , Chiang Mai, Thailand

Dr.Siwiga Dusadenoad
DEAN
GRADUATE SCHOOL OF APPLIED STATISTICS
NATIONAL INSTITUTE OF DEVELOPMENT ADMINISTRATION

Prof. Dr. Torranin Chairuangsri
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FACULTY OF SCIENCE
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The 7th International Conference on Applied Statistics 2024 (ICAS2024)

Presenter

Chiang Mai 2024

Prapawan Chomphuwiset

Mahasarakham University

Oral Presentation Schedule

Thursday 24 October 2024

TIME	Doi Sutep 1	Doi Sutep 2	Doi Nua
Session Chairperson	Monthira Duangsaphon	Teerawat Simmachan	**Wanrudee Skulpakdee**
13.00 - 14.45	**Topic:** Comparing More Than Two Populations of Survival Curves Using Chi-Squared Test **Author:** *Udomlux Kiatchupipat (page 1)*	**Topic:** A Blockchain-Based Citizen Wallet as An Alternative Approach to Leverage Digital Lending by Credit Guarantee Under the Context of Thai Sme **Authors:** *Sittikorn Direksoonthorn, Tirapot Chandarasupsang and Annop Thananchana (page 6)*	**Topic:** Dependency and Risk Spillover of China's Industrial Structure under the ESG Sustainable Development Framework **Authors:** *Yucui Li, Prapawan Chomphuwiset, Supawadee Wichitchan and Piyapatr Busababodhin (page 11)*
	Topic: Two-Parameter Half-Logistic Distribution with Applications to Survival Data **Authors:** *Yadapa Chotedelok, Nitasanee Chalemngam and Chanakarn Jomsatian (page 2)*	**Topic:** Factors Influencing Student' Acceptance of Generative AI in Higher Education: Using the UTAUT Model **Authors:** *Tianjing Xin and Worawit Tepsan (page 7)*	**Topic:** Empowering the Grid: Peer-to-Peer Energy Trading Models and Implications **Authors:** *Muhammad Ilyas, Naret Suyaraj and Chakkrapong Kuensaen (page 12)*
	Topic: The Truncated Moyal Distribution **Authors:** *Petchsri Sritiraj and Jiraphan Suntornchost (page 3)*	**Topic:** A Comparative Evaluation of Classification Models for SME Credit Risk Assessment **Authors:** *Piyada Wongwiwat and Wikanda Phaphan (page 8)*	**Topic:** Effectiveness of Automated Trading Systems Using LWMA, Stochastic, and Williams %R on SET50 Index Futures: A Study on Short Timeframes in Bearish Market Conditions **Authors:** *Pukkapon Waree, Kittipob Saetia and Jiraphat Yokrattanasak (page 13)*
	Topic: Bayesian Estimation For The Partly-Exponential Distribution **Authors:** *Nalattaporn Roopmok and Monthira Duangsaphon (page 4)*	**Topic:** Gradient Descent Decision Tree Algorithm and Nonlinear Programming for Credit Risk Assessment and Credit Strategy **Authors:** *Guoqing Chen, Piyapatr Busababodhin, Nipaporn Chutiman and Tossapol Phoophiwfa (page 9)*	**Topic:** Tourism Route Planning via Goal Programming and Multi-Objective Linear Programming: A Case Study in Bangkok **Authors:** *Chanida Leelayutto, Kannapha Amaruchkul, Sarawut Jansuwan, Siwiga Dusadenoad and Akkaranan Pongsathornwiwat (page 14)*
	Topic: B-Spline-Based Detrended Fluctuation Analysis: A Simulation and Its Application to the Daily Returns of the SET Index **Author:** *Keerati Suibkitwanchai (page 5)*	**Topic:** Ensemble Techniques for Predicting Binary Missing Class Using Real-Life Datasets **Authors:** *Muhammad Asif and Klairung Samart (page 10)*	**Topic:** A 2-Tuple Linguistic-based Multi-Criteria Decision-Making Model for E-Commerce Logistics Provider Selection Problem **Authors:** *Akkaranan Pongsathornwiwat and Kanit Chankijpanich (page 15)*

Topic waiting for abstract file

Dependency and Risk Spillover of China's Industrial Structure under the ESG Sustainable Development Framework

Yucui Li, Prapawan Chomphuwiset, Supawadee Wichitchan and
Piyapatr Busababodhin*

Department of Mathematics, Faculty of Science, Mahasarakham University,
Maha Sarakham 44150, Thailand
*Corresponding Author Email: piyapatr.b@msu.ac.th

Abstract

With increasing global focus on sustainable development goals, Environmental, Social, and Governance (ESG) factors have become critical considerations in formulating economic policies and strategies. This study applies the Vine-Copula model and CoVaR method to examine the dependence structure and risk spillover paths among different industrial sectors in China under the ESG framework. By modeling the complex interdependencies between sectors, this research reveals the relationship of each industry with the ESG benchmark index and the correlations among various sectors. It also measures the risk contagion effects of different industries under extreme market conditions and outlines the pathways of risk spillovers. Empirical results indicate that industries such as agriculture, energy, and manufacturing exhibit significant systemic risk characteristics in response to ESG fluctuations. Their high CoVaR values suggest substantial potential for risk contagion among these sectors. Additionally, sectors such as real estate, finance, and information technology show notable risk spillover paths, making them vulnerable to shocks when extreme events occur in other industries.
These findings provide data support and a theoretical foundation for the formulation of ESG policies. The study suggests that effective risk management, promotion of green finance, encouragement of technological innovation, and optimization of industrial structures can significantly reduce systemic risks, maintain the stability of industrial structures, and foster sustainable economic development.

Keywords: Industrial Structure, ESG, Vine-Copula, Dependency, Risk Spillover

REFERENCES

BIOGRAPHY

NAME	Li Yucui
DATE OF BIRTH	1986.05.05
PLACE OF BIRTH	Guangxi, China
ADDRESS	Guangxi MINZU Normal University, 23 Fozi Road, Chengnan District, Chongzuo City, Guangxi
POSITION	23 Fozi Road, Chengnan District, Chongzuo City, Guangxi
PLACE OF WORK	Guangxi MINZU Normal University
EDUCATION	2004.09-2008.07 Bachelor degree in finance, Central South University; 2008.09-2011.07 Master of Business Administration, Guilin University of Electronic Technology 2021.11-2025.04-Doctor of Philosophy in Statistical Management Science, Mahasarakham University,Thailand