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# Investigating Dependence Structure Among Subsectors of Technology Stocks: A Vine Copula Approach

**Haoran Xu [1,*], Jianing Chen [1], Hua Lin [2] and Poshan Yu [3]**

[1] Independent Researcher, Suzhou 215006, China; chenjn0929@outlook.com (J.C.)
[2] emlyon business school, Shanghai Campus, Shanghai 201199, China; linhua_shh@hotmail.com
[3] Business School, Soochow University, Suzhou 215006, China; samyu@suda.edu.cn
* Correspondence: xhr0316@outlook.com

**Abstract:** The rising popularity of technology stocks, driven by their substantial returns, underscores the importance of comprehensively understanding the interdependencies among various technological subsectors. This research employs the vine copula model to analyze the complex interdependence among different segments of the technology industry. The results indicate that the C-vine model demonstrates superior effectiveness in capturing the dependence structures within the dataset, outperforming both the R-vine and D-vine structures. This superior performance is crucial for accurately mapping the intricate relationships that define the technology sector. Furthermore, through an exhaustive investigation of 25 specific technological subsectors, the study emphasizes the critical significance of smart grids, smart factories, robotics, and future payment systems. These findings highlight the pivotal role these subsectors play in the broader technology landscape. The enhanced understanding provided by the C-vine model offers valuable insights for investors and policymakers, aiding in the navigation of the rapidly evolving technological environment.

**Keywords:** dependence structure; technology stock; sectoral market; stochastic model; vine copula

## 1. Introduction

Technology stocks have garnered significant investor attention due to their superior performance across all industry sectors. Rapid advancements in technology have fueled substantial growth in tech companies, resulting in significant returns on investment (Emir Hidayat et al., 2022). Innovations in fields such as artificial intelligence, cloud computing, and cybersecurity have not only created new markets but also enhanced existing revenue streams, thereby increasing investor confidence (Ge et al., 2024; Sharma et al., 2024). Moreover, anecdotal evidence suggests that the technology sector has shown remarkable resilience during economic downturns (BenSaïda & Litimi, 2021; Hossain et al., 2023). Additionally, the tech sector's potential for future growth, driven by continuous innovation and the emergence of new technologies, positions it as a compelling investment choice for those seeking long-term wealth accumulation. However, over the long term, the technology sector exhibits behavioral patterns closely aligned with the global stock market (Rašiová & Árendáš, 2023).

The investigation of dependence structures across diverse markets is pivotal in understanding risk contagion (Zheng et al., 2023). Copula methodologies have been increasingly employed to explore these structures across equity (Aslam et al., 2023; Chang, 2023), bond (Ejaz et al., 2022), commodity (Dai et al., 2023; Xiao et al., 2023), and currency (BenSaïda, 2023) markets. Understanding dependence structures within the technology stock market is crucial for informed decision-making and maintaining financial resilience. Recognizing how stocks move relative to each other allows investors to mitigate risk through effective asset allocation (Yu et al., 2024b). Moreover, understanding these dependencies aids in predicting market trends and systemic risks, given the tech sector's high interconnectedness (Stover et al., 2024). This interconnectedness means shocks to one company can impact others, leading to broader market implications (Torrado, 2021) and necessitating robust regulatory oversight. While Yu et al. (2024a) have examined dependence structures across ten tech sectors, there remains a gap in the literature regarding detailed analyses of individual technology-related stocks. Research is needed to better understand the nature of subsectors within the technology stock market.

To address this gap, this paper employs the vine copula model to examine the dependence structure among twenty-five technology subsectors (Xu et al., 2024). The results of this research indicate that the C-vine model demonstrates superior effectiveness in capturing the subtle connections within the dataset, outperforming both the R-vine and D-vine models. Furthermore, the study emphasizes the critical significance of smart grids, smart factories, robotics, and future payment systems. These subsectors are identified as pivotal due to their substantial influence on the overall performance and innovation within the technology industry. This study makes a significant contribution to the field by analyzing tech stocks from a sub-sectoral perspective. The results reveal notable interrelationships, carrying profound implications for both investors and policymakers. For investors, these insights can improve portfolio diversification and risk management strategies. For policymakers, understanding these dependencies is crucial for developing regulations that ensure market stability and mitigate systemic risks.

The remainder of this paper is designed as follows. Section 2 reviews the work in related literature. Sections 3 and 4 present the data and methodology, respectively. Section 5 discusses the empirical results. Section 6 concludes the findings.

## 2. Literature Review

R-vine proposed by Bedford & Cooke (2002) models dependencies among variables through a sequence of bivariate conditional distributions, offering significant flexibility for high-dimensional datasets. Aas et al. (2009) introduced two specific types of R-vines: C-vine and D-vine. The C-vine structure simplifies modeling with a canonical decomposition, facilitating interpretation, whereas the D-vine structure emphasizes dissimilarity measures, making it useful for clustering and classification tasks. Although R-vines are flexible, they are inherently complex; C-vines offer simplicity, and D-vines focus on dissimilarity modeling.

Intuitively, the flexible R-vine can be the most appropriate choice for modeling dependence structures. While it is often deemed appropriate, Czado et al. (2013) argued that the choice of vine model should be contextual. Specifically, C-vines may be preferable when one variable exhibits exceptionally high correlations with all others, whereas D-vines are more suitable for multivariate datasets where a subgroup of variables is closely related to the rest. Schepsmeier (2019) also supported the use of R-vine and C-vine models in financial contexts. Numerous studies have investigated these three structures to determine the most effective model for market dependence structures, as summarized in Table A1. Through comparative analysis, researchers aim to identify the optimal vine model for such purposes. Hernandez et al. (2017) found that R-vine models are optimal for capturing dependence among stocks in the retail and gold mining sectors, while D-vine models perform better for the manufacturing stock portfolio in Australia. Similarly, Sukcharoen & Leatham (2017) concluded that the D-vine copula approach is more suitable than the C-vine for hedging related assets in the Australian refinery sector. Czado (2019) focused on the dependence structures among stock sectors in Germany, highlighting that the C-vine copula provides the best fit. Jia Wang & Wang (2024) demonstrated that the R-vine copula is superior to both C- and D-vines for modeling dependence structures within international stock markets. Specifically, for tech stock, Yu et al. (2024a) examined dependence structures across ten tech sectors and showed that the C-vine outperforms R-vine and D-vines. They also suggested that intelligent infrastructure is the most crucial sector, with significant reliance on smart transportation and advanced manufacturing. This could also suggest that the dependence structure among tech subsectors might be better suited for C-vine.

## 3. Data

To assess the performance of technology stocks in the context of Industry 4.0, researchers commonly rely on the S&P Kensho New Economy Sector Indices, as extensively referenced in academic literature (Ghaemi Asl et al., 2023; Shrestha et al., 2023; Yaqoob & Maqsood, 2024). These indices serve as proxies for ten specific technology subsectors. Table 1 provides a concise overview of these indices. Data spanning from June 2018 to May 2024 are sourced from www.spglobal.com/spdji/. All data points are transformed into logarithmic percentage returns using the formula $r_t = ln(P_t/P_{t-1}) \times 100$. Computational tasks are conducted using the R programming language.

Table 2 reports the descriptive statistics for all return series. The descriptive statistics provide crucial insights into the performance and characteristics of various technology subsectors. The mean returns are predominantly positive, indicating general growth across subsectors, with VR having the highest mean return (0.072). Conversely, AF exhibits a negative mean return (−0.028), suggesting an overall decline in this subsector. Standard deviations highlight varying levels of volatility, with DL showing significant volatility (3.575) and SG displaying relatively low volatility (1.853). The skewness values are primarily negative, indicating a tendency towards negative returns, except for DL and NT, which exhibit slight positive skewness. Kurtosis values exceeding 3 suggest that most subsectors exhibit leptokurtic distributions, characterized by heavy tails and a propensity for extreme returns. The significant J-B test statistics across all subsectors reject the hypothesis of normality. The significant ADF test statistics confirm the stationarity of the return series. High L-B and ARCH test statistics indicate the presence of significant autocorrelation and heteroskedasticity, respectively. These findings underscore the necessity of employing the vine copula to accurately capture the complex dependencies among technology subsectors.

The correlation heatmap in Figure 1 indicates strong positive relationships among various technology subsectors. Notably, VR and SF (0.863) and VR and TP (0.803) exhibit very high correlations, suggesting these subsectors often move together. SM and AF (0.710) also show a strong positive correlation, indicating similar performance trends. Moderate correlations like SF and FP (0.788) and SG and VR (0.779) highlight significant, albeit less extreme, co-movement. Lower positive correlations, while still indicating synchronized movements, suggest diverse performance dynamics across subsectors.

**Table 1.** Summary of variables.

| Index | Subsector | Abbreviation |
|---|---|---|
| S&P Kensho Distributed Ledger Index | Distributed Ledger | DL |
| S&P Kensho Virtual Reality Index | Virtual Reality | VR |
| S&P Kensho Digital Health Index | Digital Health | DH |
| S&P Kensho Sustainable Farming Index | Sustainable Farming | SM |
| S&P Kensho Alternative Finance Index | Alternative Finance | AF |
| S&P Kensho Enterprise Collaboration Index | Enterprise Collaboration | EC |
| S&P Kensho Smart Factories Index | Smart Factories | SF |
| S&P Kensho Future Payments Index | Future Payments | FP |
| S&P Kensho Space Index | Space | SP |
| S&P Kensho Wearables Index | Wearables | WA |
| S&P Kensho Electric Vehicles Index | Electric Vehicles | EV |
| S&P Kensho Digital Communities Index | Digital Communities | DC |
| S&P Kensho Advanced Transport Systems Index | Advanced Transport Systems | AT |
| S&P Kensho Robotics Index | Robotics | RB |
| S&P Kensho Autonomous Vehicles Index | Autonomous Vehicles | AV |
| S&P Kensho Cleantech Index | Cleantech | CT |
| S&P Kensho Cyber Security Index | Cyber Security | CS |
| S&P Kensho 3D Printing Index | 3D Printing | TP |
| S&P Kensho Smart Borders Index | Smart Borders | SB |
| S&P Kensho Genetic Engineering Index | Genetic Engineering | GE |
| S&P Kensho Drones Index | Drones | DR |
| S&P Kensho Clean Energy Index | Clean Energy | CE |
| S&P Kensho Smart Grids Index | Smart Grids | SG |
| S&P Kensho Smart Buildings Index | Smart Buildings | SD |
| S&P Kensho Nanotechnology Index | Nanotechnology | NT |

**Table 2.** Descriptive statistics.

| | Mean | Max. | Min. | Std. Dev. | Skew. | Kurt. | J-B | ADF | L-B | ARCH |
|---|---|---|---|---|---|---|---|---|---|---|
| DL | 0.018 | 16.242 | −14.440 | 3.575 | 0.244 | 2.053 | 278.556*** | −11.232*** | 31.439** | 224.314*** |
| VR | 0.072 | 13.061 | −16.134 | 2.379 | −0.042 | 4.276 | 1144.110*** | −11.564*** | 65.801*** | 335.999*** |
| DH | 0.014 | 8.161 | −15.837 | 1.816 | −0.498 | 5.606 | 2027.703*** | −11.388*** | 69.376*** | 314.811*** |
| SM | 0.015 | 8.459 | −14.884 | 1.903 | −0.813 | 7.013 | 3241.280*** | −10.783*** | 85.059*** | 435.891*** |
| AF | −0.028 | 9.698 | −14.691 | 2.111 | −0.274 | 3.168 | 646.582*** | −10.717*** | 49.350*** | 341.850*** |
| EC | 0.063 | 11.764 | −12.289 | 2.171 | −0.187 | 2.437 | 380.016*** | −12.639*** | 34.139** | 253.387*** |
| SF | 0.035 | 12.737 | −11.629 | 1.912 | −0.143 | 5.130 | 1651.046*** | −10.656*** | 90.358*** | 334.573*** |
| FP | 0.032 | 9.534 | −15.271 | 1.876 | −0.687 | 6.161 | 2491.944*** | −11.043*** | 99.278*** | 524.380*** |
| SP | 0.031 | 10.089 | −14.918 | 1.564 | −0.909 | 12.596 | 10130.282*** | −11.317*** | 142.459*** | 676.356*** |
| WA | 0.037 | 8.948 | −12.527 | 1.860 | −0.362 | 4.085 | 1076.369*** | −12.402*** | 74.255*** | 252.598*** |
| EV | 0.016 | 10.755 | −12.926 | 2.270 | −0.178 | 2.893 | 531.456*** | −10.541*** | 52.553*** | 298.878*** |
| DC | 0.016 | 14.394 | −11.257 | 2.000 | −0.008 | 3.108 | 604.012*** | −12.419*** | 33.378** | 206.355*** |
| AT | −0.001 | 14.422 | −15.861 | 2.125 | −0.322 | 6.481 | 2653.095*** | −11.116*** | 88.279*** | 336.432*** |
| RB | 0.032 | 10.334 | −12.856 | 1.580 | −0.601 | 7.468 | 3578.016*** | −11.050*** | 148.705*** | 515.569*** |
| AV | 0.017 | 10.112 | −15.559 | 2.203 | −0.353 | 3.288 | 707.538*** | −10.862*** | 58.527*** | 334.551*** |
| CT | 0.052 | 13.425 | −15.611 | 2.813 | −0.125 | 2.901 | 530.307*** | −10.818*** | 52.957*** | 271.079*** |
| CS | 0.045 | 8.052 | −10.985 | 1.540 | −0.565 | 5.257 | 1807.852*** | −11.878*** | 108.072*** | 469.912*** |
| TP | −0.006 | 18.504 | −12.517 | 2.418 | 0.105 | 4.328 | 1174.393*** | −10.544*** | 53.448*** | 260.435*** |
| SB | 0.041 | 8.509 | −12.657 | 1.527 | −0.858 | 9.285 | 5575.568*** | −11.068*** | 133.475*** | 656.291*** |
| GE | −0.021 | 9.514 | −15.436 | 2.299 | −0.260 | 2.482 | 402.000*** | −11.964*** | 45.737*** | 306.720*** |
| DR | 0.039 | 8.861 | −13.343 | 1.842 | −0.539 | 6.944 | 3088.326*** | −11.717*** | 93.247*** | 404.433*** |
| CE | 0.017 | 9.877 | −12.707 | 1.551 | −0.826 | 11.569 | 8540.848*** | −10.881*** | 121.851*** | 657.796*** |
| SG | 0.014 | 11.098 | −13.366 | 1.853 | −0.464 | 6.448 | 2654.145*** | −10.838*** | 129.576*** | 538.457*** |
| SD | 0.018 | 10.559 | −11.755 | 1.696 | −0.294 | 5.140 | 1674.027*** | −10.976*** | 103.863*** | 436.509*** |
| NT | 0.014 | 11.652 | −10.812 | 2.087 | 0.110 | 2.971 | 554.950*** | −11.376*** | 68.492*** | 335.810*** |

Note: *** and ** denote statistical significance at 1% and 5% levels, respectively.

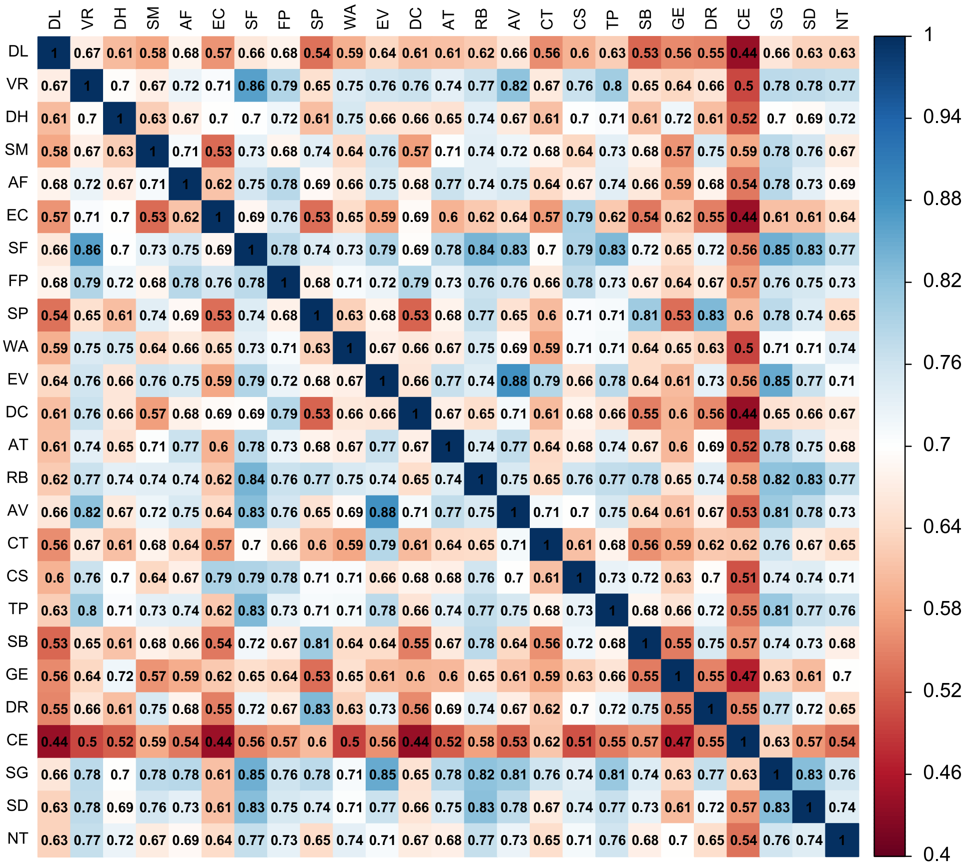


**Figure 1.** Correlation heatmap among tech subsectors.

## 4. Methodology

### *4.1. Marginal Distribution Model*

Before modeling the vine copula, we use the ARMA-GJR-GARCH model with skewed t-distributed innovations to capture the characteristics of autocorrelations and heteroscedasticity in return series. After reducing noise, the standardized residuals are extracted. The general form of the ARMA(*p*,*q*)-GJR-GARCH(*m*,*n*) filter is described as follows:

$$r_{i,t} = \sum_{j=1}^{p} \phi_j \, r_{i,t-j} + \sum_{j=1}^{q} \theta_j \, \xi_{i,t-j} + \xi_{i,t} \tag{1}$$

$$\sigma_{i,t}^2 = \omega_i + \sum_{j=1}^{m} \alpha_j \, \xi_{i,t-j}^2 + \sum_{j=1}^{m} \gamma_j \, \xi_{i,t-j}^2 \mathcal{I}_{i,t-j} + \sum_{j=1}^{n} \beta_j \, \sigma_{i,t-j}^2 \tag{2}$$

$$\xi_{i,t} = \sigma_{i,t} z_{i,t} \tag{3}$$

$$z_{i,t} \sim skew\text{-}t(\nu, \eta) \tag{4}$$

where $r_{i,t}$ is return series, $z_{i,t}$ is standardized residuals, $\sigma_{i,t}$ indicates the conditional volatility. *p*, *q*, *m*, and *n* represent non-negative integers, $\phi_j$ and $\theta_j$ denote the autoregressive and moving average coefficients. $\omega_j$, $\alpha_j$, $\gamma_j$, and $\beta_j$ are the conditional variance parameters to be estimated. $\mathcal{I}_{i,t-j}$ is an indicator function that takes one if $\xi_{i,t-j} < 0$ and zero otherwise.

Then, a copula is defined as a multivariate cumulative distribution function where each marginal distribution is uniformly distributed over the interval [0, 1]. We begin by assuming that all cumulative distributions of the return series are continuous and monotonically increasing. For copula modeling, we then use the skewed t cumulative distribution function for probability integral transformation as

$$\mu_{i,t} := T_{\nu,\eta}(z_{i,t}) \tag{5}$$

where $T_{\nu,\eta}(\cdot)$ is the skew t distribution function with estimated parameters.

*4.2. Vine Copula Model*

Bedford & Cooke (2002) introduced the vine copula approach, extending its application to multivariate contexts. This model is valued for its flexibility and the broad selection of copula families it offers. An $n$-dimensional random vector generates $n-1$ tree structures and $n(n-1)$ pairs of random variables, each characterized by pair-copula functions. Based on Sklar (1959), for a set of $n$ random variables $x = (x_1, x_2, \dots, x_n)$ with continuous and strictly increasing marginal distributions, the joint cumulative distribution function $F(x_1, x_2, \dots, x_n)$ can be represented exclusively in terms of its marginals as

$$F(x_1, x_2, \dots, x_n) = C(u_1, u_2, \dots, u_n) \tag{6}$$

where $u_i = F_i(x_i), i = 1, \dots, n$ are the transformed values of $x_1, x_2, \dots, x_n$ using the marginal distribution functions $F_i(x_i)$. The uniquely determined copula function $C(\cdot)$ can be formally defined as

$$C(u_1, u_2, \dots, u_n) = F\left(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots, F_n^{-1}(u_n)\right) \tag{7}$$

where $F_i^{-1}(u_i)$ represents the value of the inverse function of the marginal distribution function $F_i(x_i)$ at $u_i$. The copula density function $c(u_1, u_2, \dots, u_n)$ can be obtained by taking partial derivatives of the copula function with respect to each variable as

$$c(u_1, u_2, \dots, u_n) = \frac{\partial^n C(u_1, u_2, \dots, u_n)}{\partial u_1 \partial u_2 \dots \partial u_n} \tag{8}$$

Subsequently, the joint density function of $x_1, x_2, \dots, x_n$ can be expressed as the product of the marginal density functions and the copula density function, represented as

$$f(x_1, x_2, \dots, x_n) = \prod_{k=1}^{n} f_k(x_k)\, c\big(F_1(x_1), F_2(x_2), \dots, F_n(x_n)\big) \tag{9}$$

where $f_k(x_k), k = 1, \dots, n$ are marginal density functions. Furthermore, the determination of the dependence structure and pairwise copula functions is guided by a constraint set. Aas et al. (2009) made significant contributions to this area by introducing the C-vine and D-vine structures. The R-vine structure has since emerged as a highly flexible general framework, integrating elements from both C-vine and D-vine structures. In an R-vine, nodes are connected in a way that allows for a diverse combination of dependency patterns seen in both C-vine and D-vine structures. Its decomposition of the joint density function is

$$f(x) = \prod_{k=1}^{n} f_k(x_k) \prod_{i=1}^{n-1} \prod_{e \in E_i} c_{j(e),k(e)|d(e)} \left(F\big(x_{j(e)}|x_{d(e)}\big), F\big(x_{k(e)}|x_{d(e)}\big)\right) \tag{10}$$

## 5. Empirical Results

*5.1. Marginal Distribution Analysis*

To remove the autocorrelation and heteroscedasticity in return series of tech stocks, we have estimated marginal ARMA-GJR-GARCH-skew-t models, selecting the optimal lag parameters based on the Bayesian Information Criterion (BIC). Table 3 presents a thorough analysis of diagnostic tests, which were employed to evaluate the adequacy of these models. Notably, the Q and $Q^2$ statistics did not reject the null hypothesis of no autocorrelation at the 10% significance level, indicating an absence of significant autocorrelation within the models. Furthermore, the ARCH-LM test results reveal no evidence of residual heteroskedasticity in the estimated marginal models, even when considered at the 10% significance level. Comparing these findings with those outlined in Table 2, we can infer that the ARMA-GJR-GARCH-skew-t models effectively capture the marginal distributions of the technology stock return series.

**Table 3.** Diagnostic tests for residuals.

| | Q | *p*-value | $Q^2$ | *p*-value | ARCH | *p*-value |
|---|---|---|---|---|---|---|
| DL | 13.462 | 0.542 | 8.892 | 0.199 | 8.602 | 0.570 |
| VR | 11.591 | 0.105 | 15.811 | 0.313 | 15.528 | 0.114 |
| DH | 8.833 | 0.102 | 15.922 | 0.548 | 12.812 | 0.234 |
| SM | 10.307 | 0.807 | 6.094 | 0.414 | 5.947 | 0.820 |
| AF | 10.212 | 0.683 | 7.443 | 0.422 | 7.344 | 0.693 |
| EC | 6.073 | 0.758 | 6.655 | 0.809 | 6.365 | 0.784 |
| SF | 15.762 | 0.836 | 5.748 | 0.107 | 5.697 | 0.840 |
| FP | 7.679 | 0.551 | 8.798 | 0.660 | 7.692 | 0.659 |
| SP | 3.419 | 0.778 | 6.428 | 0.970 | 6.299 | 0.790 |
| WA | 11.426 | 0.932 | 4.308 | 0.325 | 6.012 | 0.814 |
| EV | 7.828 | 0.710 | 7.165 | 0.646 | 7.299 | 0.697 |
| DC | 11.679 | 0.707 | 7.198 | 0.307 | 6.997 | 0.726 |
| AT | 11.199 | 1.000 | 1.127 | 0.342 | 1.127 | 1.000 |
| RB | 7.118 | 0.998 | 1.757 | 0.714 | 1.694 | 0.998 |
| AV | 14.177 | 0.836 | 5.746 | 0.165 | 5.730 | 0.837 |
| CT | 9.567 | 0.983 | 2.946 | 0.479 | 2.944 | 0.983 |
| CS | 8.818 | 0.975 | 3.237 | 0.549 | 3.184 | 0.977 |
| TP | 9.934 | 0.077 | 16.875 | 0.446 | 15.776 | 0.106 |
| SB | 10.154 | 0.836 | 5.748 | 0.427 | 5.855 | 0.827 |
| GE | 9.598 | 0.682 | 7.453 | 0.476 | 7.708 | 0.657 |
| DR | 6.651 | 0.908 | 4.743 | 0.758 | 4.740 | 0.908 |
| CE | 9.370 | 0.992 | 2.445 | 0.497 | 2.451 | 0.992 |
| SG | 13.217 | 0.799 | 6.187 | 0.212 | 5.787 | 0.833 |
| SD | 15.454 | 0.445 | 9.951 | 0.116 | 9.522 | 0.483 |
| NT | 9.697 | 0.479 | 9.570 | 0.468 | 8.748 | 0.556 |

Note: The adjacent "*p*-value" column on the left corresponds to the test on the right.

### *5.2. Dependence Structure Analysis*

To comprehensively understand dependence structure within tech sectors, this study employs R-, C-, and D-vine methods, leveraging their distinct features. Figures 2 to 4 respectively show the first four tree structures of the R-vine, C-vine, and D-vine models. Due to the practical applicability and complexity of the vine structure for the 25 variables, we mainly analyze the first and second tree structures.

In the first layer of the R-vine, four star-shaped nodes are generated: FP, SF, RB, and SG. Among these, SF is the most central node, connecting directly to the other three nodes. For RB, two additional chain structures are formed: the first chain includes SB, SP, and DR, while the second chain consists of WA, DH, and GE. In the structure centered around SG, EV forms its own small star-shaped configuration. Additionally, SD, CE, AT, and SM are directly connected to SG, highlighting SG's role as a central hub in this layer. This arrangement in the first tree layer demonstrates the intricate and hierarchical dependencies among the subsectors, emphasizing the importance of SF and SG as key nodes in the network. In the second tree structure, SG, RB, and SG, SF become two important star-shaped nodes in the network. The rest of the structures mainly consist of chain-like formations connected to these two nodes. At the ends of these chain structures, VR, FP and SG, EV form smaller nodes. This setup highlights the central roles of SG, RB, and SF in the network, with the smaller nodes indicating additional layers of dependency at the periphery of the main structure.

In the first tree structure of the C-vine, SG stands out as the central node for all 25 tech subsectors, underscoring its crucial role within the network. Each of the other 24 subsectors is directly connected to SG, with each connection exhibiting a moderate level of dependence. This central position of SG highlights its significant influence across the entire network of tech subsectors. Moving to the second tree structure, both SG and FP emerge as key central nodes. This indicates that the dependence relationship between FP and SG extends its impact to other combinations within the network. The emergence of SG and FP as central nodes in the second layer suggests that any changes in their interdependence could have wide-reaching effects on the overall structure. This setup emphasizes not only the pivotal role of SG but also highlights the critical influence of the

SG-FP relationship in shaping the broader dependence dynamics among the tech subsectors. Such a hierarchical and layered understanding of dependence relationships is essential for comprehensive risk management and strategic decision-making in financial applications.

In the first tree structure of the D-vine, GE and CE are positioned at the ends of the chain, indicating their lower dependence on other subsectors. As the central nodes of the chain, the dependencies among variables are approximately between 0.5 and 0.6, showing very similar dependencies between subsectors. For instance, pairs like (SB, SP) and (CS, EC) exhibit dependence values of 0.0.55 and 0.59, respectively, highlighting strong direct relationships between these subsectors. This demonstrates a closely-knit network of dependencies within the core of the chain. Overall, the first tree structure effectively establishes the primary dependency network by illustrating the direct relationships among subsectors. In the second tree structure, GE and DH, as well as CT and CE, are positioned at the ends of the chain. This positioning further underscores their relatively lower dependence when considering conditional relationships. The dependencies in this layer continue to reflect the nuanced interconnections among the subsectors, revealing how certain nodes maintain lower overall dependence even as conditional factors are considered. This layered approach helps to provide a deeper understanding of the dependencies within the network, highlighting both direct and conditional relationships.

Table 4 provides the AIC, BIC, and log-likelihood values for three estimated vine copula models. The C-vine model demonstrates the lowest values for both AIC and BIC, followed by the R-vine method. Additionally, the log-likelihood values indicate that the C-vine method offers the best fit to the data, while the D-vine method exhibits the poorest fit. Subsequently, the Vuong test (Vuong, 1989) and Clarke test (Clarke, 2007) are employed for pairwise comparisons of the vine structures. The results of the Clarke and Vuong tests, with and without Akaike and Schwarz corrections as shown in Table 4, indicate that at the 1% significance level, both the R-vine and C-vine models significantly outperform the D-vine model. Furthermore, the tests also suggest the superiority of the C-vine structure over the R-vine at the 1% significance level, with the exception of the Schwarz-corrected Vuong test. Notably, in our study, the C-vine copula model surpasses both the R-vine and D-vine models within the context of the tech sector, attributable to strong mutual correlations, corroborating the findings of Yu et al. (2024a). Contrary to previous studies, the R-vine structure, despite its higher flexibility, may not always represent the optimal choice.

**Table 4.** Model comparison for different vines.

| **Vine** | **AIC** | | **BIC** | **Log-likelihood** | | |
|---|---|---|---|---|---|---|
| R-vine | −47242.43 | | −45983.04 | 23858.21 | | |
| C-vine | −47566.69 | | −46142.57 | 24051.35 | | |
| D-vine | −46638.61 | | −45124.15 | 23604.31 | | |
| **Combination** | **Clarke test** | | | **Vuong test** | | |
| | **No** | **Akaike** | **Schwarz** | **No** | **Akaike** | **Schwarz** |
| R-vine versus C-vine | 642*** | 657*** | 680*** | −3.146*** | −2.641*** | −1.299 |
| R-vine versus D-vine | 810*** | 825*** | 865*** | 3.957*** | 4.706*** | 6.693*** |
| C-vine versus D-vine | 895*** | 900*** | 910*** | 6.049*** | 6.279*** | 6.890*** |

Notes: The tests proposed by Vuong (1989) and Clarke (2007) allow to compare non-nested models. The Clarke and Vuong test statistics can be corrected for the number of parameters used in the models. In addition to normal statistics, the Akaike and Schwarz corrected statistics, representing penalty terms in AIC and BIC, are also reported. *** denotes statistical significance at 1% level.

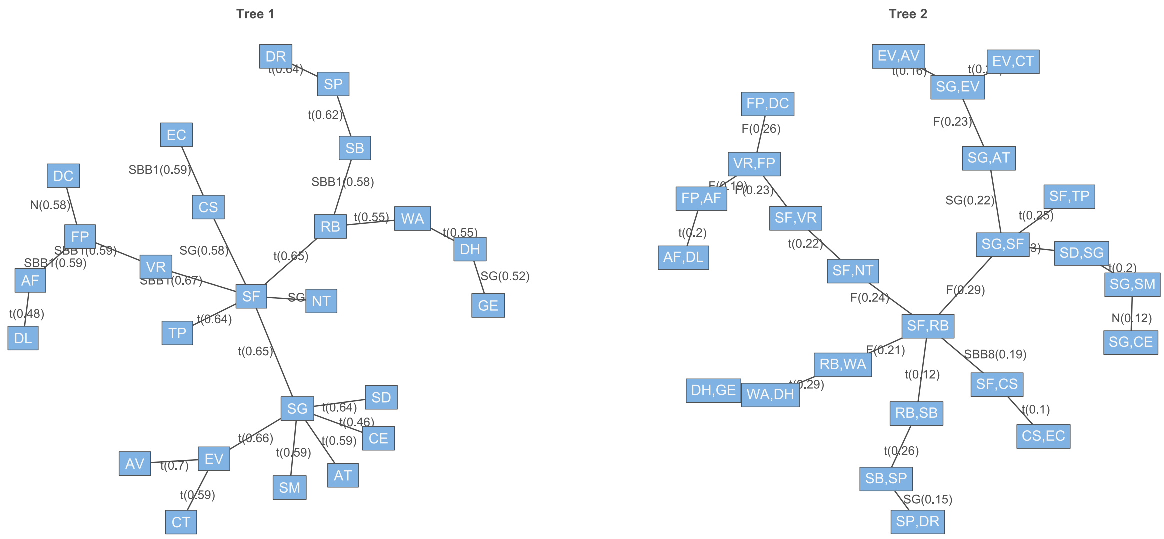


**Figure 2.** The first and second tree structures of estimated R-vine.

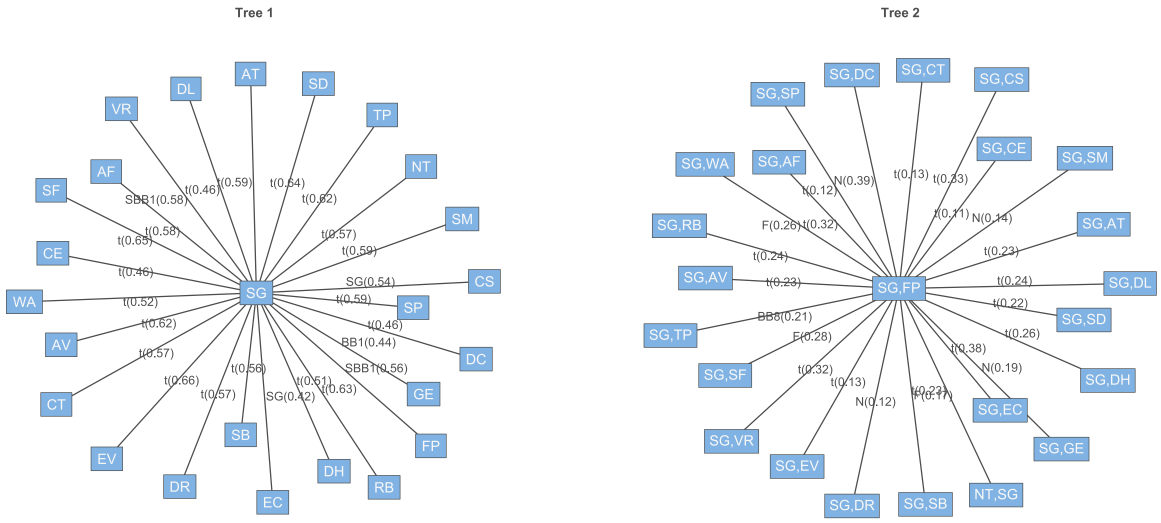


**Figure 3.** The first and second tree structures of estimated C-vine.

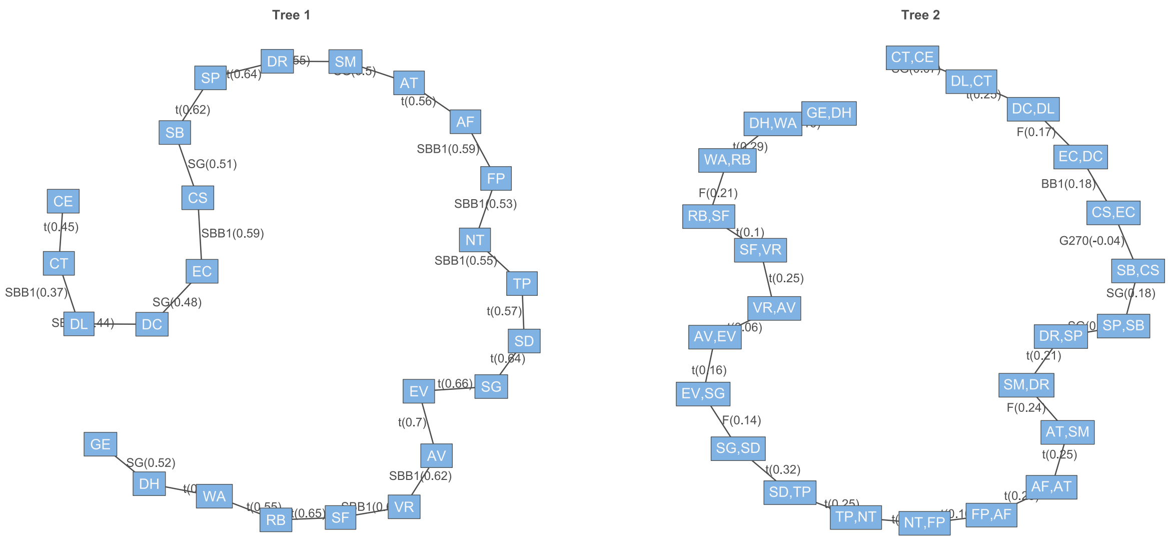

**Figure 4.** The first and second tree structures of estimated D-vine.

## 6. Conclusions

This paper applies vine copula models (the R-vine, C-vine, and D-vine) to analyze the dependence structure across twenty-five distinct technology subsectors. The findings of this research reveal that the C-vine model excels in capturing the nuanced connections within the dataset, surpassing the performance of both the R-vine and D-vine models. This enhanced capability of the C-vine model is essential for accurately depicting the intricate interdependencies that characterize the technology sector. Additionally, the study underscores the crucial importance of smart grids, smart factories, robotics, and future payment systems. These subsectors are recognized as pivotal due to their significant impact on the overall performance and innovation within the technology industry. Smart grids enhance energy efficiency and sustainability, smart factories revolutionize manufacturing processes through automation and advanced analytics, robotics improve productivity and precision across various applications, and future payment systems are reshaping the financial landscape with innovative, secure, and efficient transaction methods. By providing a comprehensive analysis of these critical subsectors, the study offers valuable insights for investors, policymakers, and industry leaders. Understanding these key areas can help stakeholders better anticipate market trends, allocate resources more effectively, and formulate strategies that leverage technological advancements. Consequently, this research not only contributes to the academic literature on technological interdependencies but also offers practical guidance for navigating the dynamic and rapidly evolving technology landscape.

However, our paper acknowledges certain limitations. Firstly, we selected a fixed sample interval, thereby disregarding the potential variations that different samples might introduce. This approach may overlook important dynamics and fluctuations present in alternative sample periods, which could provide a more comprehensive understanding of the dependence structure. Secondly, we exclusively utilized the ARMA-GJR-GARCH model to construct the marginal distribution. While this model is robust, relying solely on it may limit the robustness and generalizability of our findings. Therefore, employing a wider range of models and methods to construct and validate the marginal distributions would provide a more thorough assessment of their validity and reliability.

In the future, the interdependence structure of the tech stock market is expected to become more complex. To address this, research should incorporate dynamic processes to examine how these dependencies change over time. Employing time-varying copula models or rolling window analyses can offer a more nuanced and adaptive understanding. Additionally, integrating artificial intelligence and machine learning techniques can enhance the analysis by identifying patterns and making predictive models more robust (Kwok et al., 2024; Mehta et al., 2023). Future studies should also explore the use of alternative models to construct and validate marginal distributions, ensuring the findings' robustness and comprehensiveness. Furthermore, expanding the dataset to include more diverse and global tech stocks can provide a broader perspective on interdependencies. Researchers could also investigate the impact of macroeconomic factors and industry-specific developments on these relationships. Lastly, collaborations with industry experts can help bridge the gap between theoretical models and practical applications, leading to more actionable insights.

## Appendix A

**Table A1.** Literature on the comparison of vine copula models.

| Authors | Vine types | Tools |
|---|---|---|
| Jia Wang & Wang (2024) | R-vine<br>C-vine<br>D-vine | No disclosure |

| | | |
|---|---|---|
| Czado & Nagler (2022) | R-vine<br>C-vine<br>D-vine | VineCopula |
| Czado (2019) | R-vine<br>C-vine<br>D-vine | Mainly VineCopula |
| Schepsmeier (2015) | R-vine<br>C-vine<br>D-vine | VineCopula |
| Schepsmeier (2019) | R-vine<br>C-vine | VineCopula |
| Brechmann & Schepsmeier (2013) | C-vine<br>D-vine | CDVine |
| Aslam et al. (2023) | R-vine<br>C-vine<br>D-vine | VineCopula |
| Jose Arreola Hernandez & Reboredo (2017) | R-vine<br>C-vine<br>D-vine | No disclosure |
| Zhang et al. (2014) | R-vine<br>C-vine<br>D-vine | No disclosure |
| Jain & Maitra (2023) | R-vine<br>C-vine<br>D-vine | VineCopula |
| Čeryová & Árendáš (2024) | R-vine<br>C-vine<br>D-vine | VineCopula |
| Sahamkhadam & Stephan (2023) | R-vine<br>C-vine<br>D-vine | No disclosure |
| Dißmann et al. (2013) | R-vine<br>C-vine<br>D-vine | VineCopula |
| Dalu Zhang & Tsopanakis (2018) | R-vine<br>C-vine<br>D-vine | VineCopula/CDvine |
| Zhang (2014) | C-vine<br>D-vine | No disclosure |
| Zhang et al. (2015) | C-vine<br>D-vine | CDVine |
| Sukcharoen & Leatham (2017) | C-vine<br>D-vine | CDVine |
| Nguyen & Liu (2023) | C-vine<br>D-vine | No disclosure |
| Jiang et al. (2021) | C-vine<br>D-vine | No disclosure |

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