Journal of
Risk and Financial Management

MDPI

Article

Can ESG Integration Enhance the Stability of Disruptive Technology Stock Investments? Evidence from Copula-Based Approaches

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

[1] Business School, Soochow University, Suzhou 215006, China
[2] Independent Researcher, Suzhou 215006, China; xhr0316@outlook.com (H.X.); chenjn0929@outlook.com (J.C.)
* Correspondence: samyu@suda.edu.cn

Abstract: This paper provides an investigation into the dependence structure among different disruptive technology sectors driving the Fourth Industrial Revolution and scrutinizes the impact of ESG integration on shaping investments in different tech stock sectors in the presence of ESG consideration, represented by the ESG stock index, versus without specific ESG consideration, represented by the general stock index. The results show that (i) C-vine outperforms R-vine and D-vine when modeling the dependence structure of tech sectors. Intelligent infrastructure is the most crucial sector, with substantial reliance on smart transportation and advanced manufacturing. (ii) ESG integration reduces dependence, especially tail dependence, between tech sectors and the stock market, which benefits the future security sector the most and future communication the least. (iii) ESG integration mitigates risk spillover between tech sectors and the stock market, particularly benefiting final frontiers and intelligent infrastructure. The decrease in downside spillover is more significant compared to upside scenarios. For downside risk, spillover from tech sectors to stock indices is more reduced than the reverse, while the opposite holds for upside risk. These sectoral findings offer insights for market participants in financial market investments, financial regulators in risk management, and listed companies in ESG disclosure.

Keywords: ESG; industrial revolution 4.0; tech stock; copula; dependence structure; spillover effect

Citation: Yu, Poshan, Haoran Xu, and Jianing Chen. 2024. Can ESG Integration Enhance the Stability of Disruptive Technology Stock Investments? Evidence from Copula-Based Approaches. *Journal of Risk and Financial Management* 17: 197. https://doi.org/10.3390/jrfm17050197

Academic Editors: Svetlozar (Zari) Rachev and Thanasis Stengos

Received: 28 February 2024
Revised: 30 April 2024
Accepted: 7 May 2024
Published: 11 May 2024

1. Introduction

Industrial Revolution 4.0 (I4.0) refers to a policy-driven transformation of industrial processes using advanced digital technologies piloted by the German government (Reischauer 2018). Over the last decade, companies have transformed manufacturing through investments in I4.0 technologies like IoT, AI, cloud computing, autonomous robots, and blockchain (Jabbour et al. 2019; Chen et al. 2020). Aside from significant contributions to social development, another primary focus of I4.0 is on environmental sustainability (Khan et al. 2023). Nowadays, with ongoing climate change and environmental degradation, environmental, social, and governance (ESG) is increasingly being used to evaluate the performance of firms and pension funds, guide investment decision-making, and inform customer purchasing. Particularly, ESG integration is an emerging investment strategy that considers ESG responsibilities when making investment decisions in the financial market. Further, regulatory developments for ESG are taking place all over the world nowadays (KPMG 2022), which are the key guidelines for investors to make ESG investments. Technology stocks within Industry 4.0 have garnered broad investor attention due to their outperformance across all industry sectors, making them an attractive long-term investment (Emir Hidayat et al. 2022). Moreover, anecdotal evidence suggests that the technology sector has exhibited remarkable resilience in economic downturns, possibly attributed to its extensive economy-wide dependency and suitability for "work from home" scenarios (BenSaïda and Litimi 2021; Hossain et al. 2023). However, in the long term, the technology sector demonstrates behavioral patterns closely aligned with the global stock market (Rašiová and Árendáš 2023).

Exploring the link between social development, environmental sustainability, and financial stability is vital for policymakers and investors. Naturally, investing in I4.0 technology companies promotes both firm development and technological advancement and indirectly fosters societal progress, which indicates that social development correlates positively with financial stability. In the extant literature, researchers have made efforts to reveal that I4.0 technologies can facilitate ESG disclosure and compliance, contributing to environmental sustainability (Alkaraan et al. 2022; Asif et al. 2023; Kumar et al. 2024). In addition, ESG-compliant companies are more likely to be favored by investors as ESG can create value for stakeholders, enhance firms' reputation, and improve firm value (Zeng et al. 2023; Chen et al. 2023). This establishes a positive correlation between environmental sustainability and social development. Nevertheless, the insufficient research on the correlation between financial stability and environmental sustainability, particularly within the tech market, underscores the need for dedicated exploration. This is crucial due to the distinctive role of technology companies in the economy. Furthermore, current studies often utilize aggregate tech stock indices or focus on specific types of technology stocks, neglecting potential heterogeneity among sectoral tech stocks. This gap necessitates a comprehensive investigation into the dependence structure among different disruptive technology sectors. Additionally, understanding the nuanced impact of ESG on the dependence and spillover effects within disruptive technology sectors and the overall market remains an underexplored research problem.

Motivated by the aforementioned points, this paper initially explores dependence structures within ten tech stock sectors using vine copula models to comprehend the transmission of risk within these sectors. Subsequently, it assesses the impact of ESG integration on financial stability by comparing dependence and risk spillover measures in the presence or absence of ESG consideration. Dynamic dependence is modeled using a t-copula with a GAS process, while dynamic, asymmetric, and heterogeneous risk spillover effects are evaluated using the copula-based CoVaR approach.

This study contributes to the literature in at least three dimensions. First, this paper explores the hitherto unexamined dependence structure of various technology sectors steering I4.0. Second, it investigates the benefit of ESG integration for tech sectors from the perspective of investors. This aspect of investigation distinguishes our research as innovative within the scholarly landscape. Third, the present study adopts a methodological refinement by utilizing sectoral data, a departure from the common reliance on aggregate indices seen in previous research. This approach offers more granular insight into the dynamics of I4.0 tech stocks, addressing a previously overlooked aspect and enhancing the specificity of our findings.

This study yields several intriguing results. First, C-vine surpasses R-vine and D-vine in modeling tech sector dependence. Intelligent infrastructure emerges as the most pivotal sector, exhibiting substantial dependence on smart transportation and advanced manufacturing. Second, ESG integration diminishes dependence, especially tail dependence, between tech sectors and the stock market, notably favoring the future security sector the most and the future communication sector the least. Third, ESG integration appears to effectively mitigate risk spillover between the technology sectors and the stock market, with a pronounced impact on final frontiers and intelligent infrastructure. Notably, the reduction in downside spillover outweighs that in upside scenarios. In the context of downside risk, spillover from tech sectors to stock indices is more notably diminished, while the reverse holds for upside risk.

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

2. Literature Review

2.1. Dependence Structure of Sectoral Markets

The dependence structure across diverse markets, which provides richer information than individual dependence coefficients, is currently a prominent focus in risk contagion (Zheng et al. 2023). An increasing number of studies have applied copula approaches to examine the presence of dependence structure across markets, including equity (Aslam et al. 2023), commodity (Xiao et al. 2023), currency (BenSaïda 2023), etc. However, most studies predominantly utilize bivariate dynamic copulas, neglecting the simultaneous modeling of high-dimensional variables. To address this limitation, Bedford and Cooke (2002) introduced the innovative multivariate copula method known as vine copula. In research employing vine copula approaches, comparison often involves three prevalent structures within the vine copula model: Regular (R-vine), Canonical (C-vine), and Drawable (D-vine) structures (Aslam et al. 2023; BenSaïda 2023; Czado 2019; Jain and Maitra 2023). The prevailing assumption in this regard favors the superior performance of R-vine, given its greater flexibility. For instance, BenSaïda (2023) suggests its appropriateness in modeling currency markets. However, Czado et al. (2013) argue that the suitability of a vine model is contextual, emphasizing that C-vine may be preferable when a variable exhibits exceptionally high correlation with all others, and D-vine fits well in multivariate datasets where a group of variables is closely related to the rest. This context-specific suitability is further supported by Arreola Hernandez et al. (2017), who found that while an R-vine model is optimal for capturing dependence between stocks in the retail and gold mining sectors, a D-vine model performs better for the manufacturing stock portfolio in Australia. Similarly, Sukcharoen and Leatham (2017) conclude that the D-vine copula approach is more suitable than C-vine for hedging related assets in the Australian refinery sector. Czado (2019) directs attention to the dependence structure among stock sectors in Germany and highlights that the C-vine copula exhibits the best fit for modeling this structure.

Based on prior research, this paper hypothesizes the following:

Hypothesis 1. *The C-vine model outperforms the R-vine (excluding the C- and D-vine) and D-vine models in the context of I4.0 tech sectors.*

2.2. ESG and Dependence

The literature identifies two primary approaches for investigating financial market dependence: (1) multivariate GARCH models like DCC (Ding et al. 2022; Dong et al. 2023; Yu et al. 2024) or BEKK (Ashfaq et al. 2023), and (2) copula theory, noted for its ability, as highlighted by Ning (2010), to detect nonlinear and asymmetric dependencies. Traditional correlation-based approaches are criticized for their limited performance in capturing complex dependence dynamics. Copula theory offers the advantage of detecting shock transmission paths among variables, a capability lacking in multivariate GARCH models, as discussed by BenSaïda and Litimi (2021). Hence, this study opts for the copula framework to model multivariate dependence.

Rašiová and Árendáš (2023) indicate that the dependence between the stock market volatility and tech stocks is strongly negative and asymmetrically increasing, with surges in market volatility. Also, specific tech stocks are studied. For instance, Ghaemi Asl et al. (2023b) studied the relationship between sectoral stocks and distributed ledger technology stocks and found significant and positive dependence, and it tends to be higher in the long term. Numerous studies examine the dependence between ESG-related assets (especially green bonds) and other financial assets and find the superiority of ESG assets in many aspects (Pham and Nguyen 2021; Duan et al. 2023; Huang et al. 2023). Also, some pay attention to the relationship between fintech and green assets. For instance, Tiwari et al. (2023) and Urom (2023) find the mostly positive and strongest dependence between fintech and green assets in the long term but weak dependence in the short term, and fintech stocks dominate most green assets.

Then, this paper hypothesizes the following:

Hypothesis 2. *ESG integration can reduce dependence between the I4.0 tech sectors and the overall stock market.*

2.3. ESG and Spillover Effects

Financial crisis contagion theory posits that economic sector interdependence and financial market openness lead to shock transmission. Forbes and Rigobon (2002) define contagion as an escalation in risk correlation or spillover effects across markets, particularly during external shocks. High-risk spillover magnitudes indicate the potential for a financial crisis outbreak, as uncertainty easily transmits between financial markets (Aloui et al. 2011).

In this context, numerous studies have devised methodologies to quantify the spillover effects of financial markets (Baruník and Křehlík 2018; Diebold and Yilmaz 2012; Antonakakis et al. 2020; Balcilar et al. 2021), primarily relying on TVP-VAR models. However, these approaches fail to capture the nonlinear relationships amid heightened global economic uncertainty, a weakness that can be addressed by copula theory. There is a scarcity of research on the risk spillover effects of ESG assets (Maraqa and Bein 2020; Gao et al. 2022). For instance, Papathanasiou et al. (2022) characterized S&P 500 ESG as a net risk transmitter in the stock market, implying heightened risk in ESG investment compared to general stock investment. Nevertheless, these studies have concentrated on spillover effects within particular markets, such as the stock market, or among ESG-related assets. Zhang et al. (2022a, 2022b) analyzed the dynamic interconnectedness of sustainability-related financial assets. Moreover, Liu et al. (2023) discovered that ESG investment generally mitigates risk spillovers across various financial markets, concurrently bolstering Chinese financial stability.

Therefore, this paper hypothesizes the following:

Hypothesis 3. *ESG integration can reduce spillover effects between the I4.0 tech sectors and the overall stock market.*

3. Methodology

To understand the nature of our data, we deeply review the descriptive statistics and first employ marginal distribution estimation of the return series. Subsequently, we then use probability integral transformation (PIT) to extract the marginal distribution's standardized information for copula model estimation. Second, to investigate Hypothesis 1, we apply the vine copula model to estimate the dependence structure among tech sectors, with the uniformly distributed series obtained by PIT. Third, we use a t-copula to estimate the joint distribution between individual sectors and the stock index, followed by a GAS process to update and obtain dynamic dependence measures of the estimated t-copulas to ultimately investigate Hypothesis 2. In the fourth step, we analyze risk spillovers using the CoVaR measure based on estimated marginal distributions and t-copulas of returns series to examine Hypothesis 3. The combination of these three models is commonly utilized in the academic literature, as demonstrated by the works of various researchers such as Dai et al. (2023), Hanif et al. (2022), Jain and Maitra (2023), Kielmann et al. (2022), Rehman et al. (2023), Yao and Li (2023), and Zeng et al. (2022), underscoring its validity and widespread acceptance in scholarly discourse. For clarity and easy reference, we have synthesized a summary of their models' application in Table A1.

3.1. Marginal Distribution Model

In this study, the ARMA-GJR-GARCH model with skewed t-distributed innovations is used to depict the characteristics of autocorrelations and heteroscedasticity in the return series and the standardized residuals are extracted after noise reduction. The ARMA(p,q)-GJR-GARCH(m,n) filter has the following general form:

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

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

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

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

where $r_{i,\,t}$ is the return series, $z_{i,\,t}$ is the standardized residuals, and $\sigma_{i,\,t}$ indicates the conditional volatility. p, q, m, and n represent non-negative integers. ϕ_j and θ_j denote the autoregressive and moving average coefficients. ω_j, α_j, γ_j, and β_j are the conditional variance parameters to be estimated. $\mathcal{I}_{i,\,t-j}$ is an indicator function that takes 1 if $\xi_{i,\,t-j} < 0$ and 0 otherwise.

In Equation (4), we assume that $z_{i,\,t}$ is an *i.i.d.* random variable with zero mean and unit variance that follows a Hansen (1994) skewed t density distribution expressed as

$$t(z_{i,\,t}|\nu,\,\eta) = \begin{cases} bc\left(1 + \frac{1}{\nu-2}\left(\frac{bz_{i,\,t}+a}{1-\eta}\right)^2\right)^{-\frac{\nu+1}{2}}, & z_{i,\,t} < -a/b \\ bc\left(1 + \frac{1}{\nu-2}\left(\frac{bz_{i,\,t}+a}{1+\eta}\right)^2\right)^{-\frac{\nu+1}{2}}, & z_{i,\,t} \geq -a/b \end{cases} \tag{5}$$

where ν and η are the degrees of freedom and symmetry parameters, respectively, with $2 < \nu < \infty$ and $-1 < \eta < 1$. The coefficients a, b, and c are constants given as

$$\begin{cases} a = 4\eta c \frac{\nu-2}{\nu-1} \\ b^2 = 1 + 3\eta^2 - a^2 \\ c = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi(\nu-2)}} \end{cases} \tag{6}$$

where $\Gamma(\cdot)$ is the Gamma function. If $\eta = 0$ and ν is finite, it converges to the symmetric Student-t distribution, whereas if $\eta = 0$ and ν is infinite, it converges to the Gaussian distribution.

Subsequently, a copula is characterized as a multivariate cumulative distribution function, wherein its individual marginal distributions uniformly span the interval [0, 1]. We first assume that all cumulative distributions of the return series are continuous and monotonically increasing. Then, for copula modeling, we utilize the skewed t cumulative distribution function for probability integral transformation, expressed as

$$\mu_{i,\,t} := T_{\nu,\,\eta}(z_{i,\,t}) \tag{7}$$

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

3.2. Vine Copula Model

According to the theorem proposed by Sklar (1959), given n random variables $x = (x_1,\,x_2,\,\ldots,\,x_n)$ with continuous and strictly increasing marginal distributions, the joint cumulative distribution function $F(x_1,\,x_2,\ldots,x_n)$ can be expressed solely in terms of its marginals as

$$F(x_1, x_2, \ldots, x_n) = C(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) = C(u_1,\,u_2, \ldots, u_n) \tag{8}$$

where $u_i = F_i(x_i),\ i = 1, \ldots, n$ are the transformed values of $x_1,\,x_2,\,\ldots,\,x_n$ using the marginal distribution functions $F_i(x_i)$, which are uniformly distributed across [0, 1]. The uniquely determined copula function $C(\cdot)$ can be formally defined as

$$C(u_1,\,u_2, \ldots, u_n) = F\left(F_1^{-1}(u_1), F_2^{-1}(u_2), \ldots, F_n^{-1}(u_n)\right) \tag{9}$$

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 $c(u_1, u_2, \ldots, u_n)$ can be obtained by taking partial derivatives of the copula function with respect to each variable in the unit interval [0, 1], which can be derived as

$$c(u_1, u_2, \ldots, u_n) = \frac{\partial^n C(u_1, u_2, \ldots, u_n)}{\partial u_1 \partial u_2 \ldots \partial u_n} \tag{10}$$

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

$$f(x_1, x_2, \ldots, x_n) = \prod_{k=1}^{n} f_k(x_k) c(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) \tag{11}$$

where $f_k(x_k)$, $k = 1, \ldots, n$ are marginal density functions.

A bivariate copula function can only characterize dependence between two variables, while Bedford and Cooke (2002) proposed the vine copula approach and extended the analysis to multivariate contexts. This model has been appreciated for their flexibility and extension of copula selection from a wide range of copula families. An n-dimensional random vector will generate $n-1$ tree structures and $n(n-1)$ pairs of random variables that need to be characterized by paired-copula functions. Additionally, the determination of the dependence structure and pairwise copula functions is facilitated by a constraint set. Aas et al. (2009) contributed to this field by introducing two notable structures known as the C-vine and D-vine. The C-vine structure exhibits a dependency pattern akin to a star configuration, wherein each variable is linked directly to a central node. Conversely, the D-vine structure depicts a sequential pathway, where each variable is connected to its immediate predecessor. Moreover, the R-vine structure emerges as a general framework offering great flexibility, as it combines elements from both the C-vine and D-vine structures. In the R-vine, nodes are interconnected in a manner that allows for a versatile amalgamation of dependency patterns observed in both C-vine and D-vine structures. Their decomposition of the joint density function is as follows:

$$f_R(x) := f(x_1, x_2, \ldots, x_n) = \prod_{k=1}^{n} f_k(x_k) \prod_{i=1}^{n-1} \prod_{e \in E_i} c_{j(e),\, k(e)|d(e)} \left(F\left(x_{j(e)} \middle| x_{d(e)}\right),\, F\left(x_{k(e)} \middle| x_{d(e)}\right) \right) \tag{12}$$

$$f_C(x) = \prod_{k=1}^{n} f_k(x_k) \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{i,\, i+j|1:(i-1)} \left(F(x_i|x_1, \ldots, x_{i-1}),\, F\left(x_{i+j}|x_1, \ldots, x_{i-1}\right) \middle| \theta_{i,\, i+j|1:(i-1)} \right) \tag{13}$$

$$f_D(x) = \prod_{k=1}^{n} f_k(x_k) \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{j,\, j+1|(j+1):(j+i-1)} \left(F\left(x_j|x_{j+1}, \ldots, x_{j+i-1}\right),\, F\left(x_{j+i}|x_{j+1}, \ldots, x_{j+i-1}\right) \middle| \theta_{j,\, j+1|(j+1):(j+i-1)} \right) \tag{14}$$

3.3. GAS t-Copula Model

Dynamic copula models exhibit time-varying dependence parameters while maintaining a constant copula function. These models are broadly classified into parameter-driven, such as stochastic copula models (Hafner and Manner 2012), and observation-driven, exemplified by ARCH-type models and related copula models (Patton 2006; Creal et al. 2013). Many studies reveal that the latter approach is superior to the former (Nguyen and Javed 2023). In particular, Koopman et al. (2016) empirically demonstrate that the generalized autoregressive score (GAS) model surpasses other observation-driven processes in predictive accuracy.

Following Creal et al. (2013), and in line with Czado (2019) and Rehman et al. (2023), time-varying dependence between the bivariate return series $r_{i,\, t}$ and $r_{j,\, t}$ is assessed while mitigating autocorrelation and heteroskedasticity effects. This involves employing innovations $z_{i,\, t}$ and $z_{j,\, t}$ which undergo a probability transformation via Equation (7) to extract series $\mu_{i,\,t}$ and $\mu_{j,\,t}$ and derive more accurate measurements of dependence. Hence, like Equation (8), the joint distribution is given by the copula function $C(\cdot)$, with parameters Θ, as

$$F\left(z_{i,\,t},\, z_{j,\,t}\right) = C\left(\mu_{i,\,t},\, \mu_{j,\,t}\middle|\Theta\right) \tag{15}$$

Initially, a suitable copula function is determined. This paper utilizes a t-copula which is a popular choice for parametric modeling in risk management and financial econometrics due to its effective fitting of the fat-tail characteristic observed in financial time series (Lourme and Maurer 2017; Zhang et al. 2022a). In addition, many studies demonstrate that the GAS t-copula model proposed by Oh and Patton (2016) has exceptional performance in depicting extreme risk (Nguyen and Javed 2023; Yao and Li 2023). The cumulative distribution and density functions of the t-copula are given by

$$C\left(\mu_{i,\,t},\, \mu_{j,\,t}\middle|\rho,\, v\right) = \int_{-\infty}^{T_v^{-1}(\mu_{i,\,t})} \int_{-\infty}^{T_v^{-1}(\mu_{j,\,t})} \frac{1}{2\pi\sqrt{1-\rho^2}} \left[1 + \frac{s^2 + t^2 - 2\rho st}{v(1-\rho^2)}\right]^{-\frac{v+2}{2}} dsdt \tag{16}$$

$$c\left(\mu_{i,\,t},\, \mu_{j,\,t}\middle|\rho,\, v\right) = \rho^{-\frac{1}{2}} \frac{\Gamma\left(\frac{v+2}{2}\right)\Gamma\left(\frac{v}{2}\right)}{\left[\Gamma\left(\frac{v+1}{2}\right)\right]^2} \frac{\left[1 + \frac{T_v^{-1}(\mu_{i,\,t})^2 + T_v^{-1}(\mu_{j,\,t})^2 - 2\rho T_v^{-1}(\mu_{i,\,t}) T_v^{-1}(\mu_{j,\,t})}{v(1-\rho^2)}\right]^{-\frac{v+2}{2}}}{\left[\left(1 + \frac{T_v^{-1}(\mu_{i,\,t})^2}{v}\right)\left(1 + \frac{T_v^{-1}(\mu_{j,\,t})^2}{v}\right)\right]^{-\frac{v+2}{2}}} \tag{17}$$

where ρ is the first parameter of the t-copula, v denotes the degrees of freedom (the second parameter), and $T_v^{-1}(\cdot)$ represents the inverse function of the univariate t distribution function. In the subsequent dynamic t-copula model, the degrees of freedom v are kept fixed, while we allow the correlation parameter ρ to vary as $\rho_{ij,\,t}$.

Then, the t-copula parameters are normalized. Since $\rho_{ij,\,t}$ is defined in the interval $(-1, 1)$, we utilize the inverse Fisher transformation ψ to transform $\zeta_t^{i,\,j} \in (-\infty,\, \infty)$ into $\rho_{ij,\,t}$. In other words, we generate $\rho_{ij,\,t}$ through the transformation of $\zeta_t^{i,\,j}$ by using ψ.

$$\rho_{ij,\,t} := \psi\left(\zeta_t^{i,\,j}\right) = \frac{e^{2\zeta_t^{i,\,j}} - 1}{e^{2\zeta_t^{i,\,j}} + 1} \tag{18}$$

The final step involves modeling the process of $\zeta_t^{i,\,j}$ based on the GAS(1,1) model. The driving equation for this process is given as

$$\zeta_t^{i,\,j} = \Omega_{i,\,j} + A_{i,\,j} s_{t-1}^{i,\,j} + B_{i,\,j} \zeta_{t-1}^{i,\,j} \tag{19}$$

where $\Omega_{i,\,j}$ represents the mean constant term, $A_{i,\,j}$ and $B_{i,\,j}$ are the parameters to be estimated, and $s_t^{i,\,j}$ denotes the scale score, expressed as follows:

$$s_t^{i,\,j} = S_{ij,\,t} \nabla_{ij,\,t} \tag{20}$$

$$\nabla_{ij,\,t} = \frac{\partial lnc\left(\mu_{i,\,t},\, \mu_{j,\,t}\middle|\rho_{ij,\,t},\, \mathcal{F}_t; \varsigma_{i,\,j}\right)}{\rho_{ij,\,t}} \tag{21}$$

$$S_{ij,\,t} = I_{ij,\,t}^{-\frac{1}{2}} \tag{22}$$

$$I_{ij,\,t} = E_{t-1}\left[\nabla_{ij,\,t},\, \nabla'_{ij,\,t}\right] \tag{23}$$

where $\varsigma_{i,\,j} = \left(\Omega_{i,\,j},\, A_{i,\,j},\, B_{i,\,j}\right)$ and $S_{ij,\,t}$ are the square roots of the inverse of the Fisher information matrix, and $\mathcal{F}_t$ is the set of information known at time t. E_{t-1} denotes an expectation regarding the corresponding copula density function $c\left(\mu_{i,\,t},\, \mu_{j,\,t}\middle|\rho_{ij,\,t},\, \mathcal{F}_t; \varsigma_{i,\,j}\right)$.

In capturing nonlinear dependence, copulas render the linear Pearson correlation coefficient inappropriate. Instead, Kendall's tau (τ) is commonly employed, which is marginally distribution-invariant and depends solely on the underlying copula. The static τ is defined as

$$\tau(r_{i,t},\ r_{j,t}) = E\left(sign\left(r_{i,\ t} - \widetilde{r}_{i,\ t}\right)\left(r_{j,\ t} - \widetilde{r}_{j,\ t}\right)\right) \tag{24}$$

where $\left(\widetilde{r}_{i,\ t},\ \widetilde{r}_{j,\ t}\right)$ is an independent pair with the same distribution as $(r_{i,t},\ r_{j,t})$. Nelsen (2006) extends the measurement of Kendall's τ by incorporating the copula function as

$$\tau(r_{i,\ t},\ r_{j,\ t}) = 4\int_0^1\int_0^1 C(\mu_{i,\ t},\ \mu_{j,\ t})dC(\mu_{i,\ t},\ \mu_{j,\ t}) - 1 \tag{25}$$

Specifically, for the dynamic t-copula, the dependence τ between $r_{i,\ t}$ and $r_{j,\ t}$ is calculated as $\tau(r_{i,\ t},\ r_{j,\ t}) = \frac{2}{\pi}arcsin(\rho_{ij,\ t})$. Additionally, we are particularly interested in the dependence among extreme events in finance, and thus, tail dependence is of interest. The important features of tail distribution and dependency are the upper and lower tail dependence coefficients (TDC) λ_l and λ_u, and the tail concentration function (TCF) $\Lambda(u)$, which are defined as follows:

$$\lambda_l = \lim_{u\to 0}\mathbb{P}\left(r_{j,t} \le F_j^{-1}(u)\middle| r_{i,t} \le F_i^{-1}(u)\right) = \lim_{u\to 0^+}\frac{C(u,\ u)}{u} \tag{26}$$

$$\lambda_u = \lim_{u\to 1}\mathbb{P}\left(r_{j,t} > F_j^{-1}(u)\middle| r_{i,t} > F_i^{-1}(u)\right) = \lim_{u\to 1^-}\frac{1-2u+C(u,\ u)}{1-u} \tag{27}$$

$$\Lambda(u) = \frac{C(u,\ u)}{u}\cdot\mathcal{I}_{0\le u\le 0.5} + \frac{1-2u+C(u,\ u)}{1-u}\cdot\mathcal{I}_{0.5<u\le 1} \tag{28}$$

where $F_i^{-1}(\cdot)$ and $F_j^{-1}(\cdot)$ are the inverse marginal distribution functions and $u \in [0,\ 1]$. Specifically, for continuously distributed random variables with the t-copula, the time-varying symmetrical tail dependence coefficient is given by

$$\lambda_{ij,\ t} = 2T_{v+1}\left(-\sqrt{v+1}\sqrt{\frac{1-\rho_{ij,\ t}}{1+\rho_{ij,\ t}}}\right) \tag{29}$$

where $T_{v+1}(\cdot)$ is the t cumulative distribution function with $v+1$ degrees of freedom.

3.4. CoVaR–Copula Approach

To quantify extreme risk spillover between tech sectors and the overall stock market, we apply the CoVaR measure proposed by Adrian and Brunnermeier (2016) to provide information on the market *VaR* under the condition of an extreme situation in another market. By incorporating the GAS process of innovations and the ARMA-GJR-GARCH description of returns into the CoVaR, we refine its capability to dynamically model time-varying dependencies and volatility fluctuations. This enhancement enables CoVaR to provide a more nuanced and precise assessment of systemic risk transmission, particularly in periods characterized by extreme market stress.

VaR represents the anticipated maximum loss of a portfolio over a specific timeframe, based on a predetermined level of confidence. In particular, let $r_{i,\ t}$ and $r_{j,\ t}$ denote the return series. Given the confidence level $1-\alpha$, the downside and the upside *VaR* for $r_{j,\ t}$ can be expressed, respectively, as

$$\mathbb{P}\left(r_{j,\ t} \le VaR^j_{\alpha,\ t}\right) = \alpha \tag{30}$$

$$\mathbb{P}\left(r_{j,\ t} \ge VaR^j_{1-\alpha,\ t}\right) = \alpha \tag{31}$$

We can further calculate the downside and upside VaR based on estimated marginal distributions as follows:

$$VaR^{j}_{\alpha,\,t} = \varpi_{j,\,t} + T^{-1}_{\nu,\,\eta}(\alpha)\sigma_{j,\,t} \tag{32}$$

$$VaR^{j}_{1-\alpha,\,t} = \varpi_{j,\,t} + T^{-1}_{\nu,\,\eta}(1-\alpha)\sigma_{j,\,t} \tag{33}$$

where $\sigma_{j,\,t}$ is the standard deviation, and $\varpi_{j,\,t}$ is the conditional mean, calculated as $\varpi_{j,\,t} = \sum_{i=1}^{p}\phi_i r_{j,\,t-i} + \sum_{i=1}^{q}\theta_i\xi_{j,\,t-i}$, of the return series. $T^{-1}_{\nu,\,\eta}(1-\alpha)$ and $T^{-1}_{\nu,\,\eta}(\alpha)$ are the $1-\alpha$ and the α-quantile of the skewed t distribution.

The downside *CoVaR* of market *i* given extreme downturns in market *j* at a confidence level of $1-\beta$ or the β-quantile of the conditional distribution of $r_{i,\,t}$ is

$$\mathbb{P}\left(r_{i,\,t} \le CoVaR^{D,\,i|j}_{\beta,\,\alpha,\,t} \middle| r_{j,\,t} \le VaR^{j}_{\alpha,\,t}\right) = \beta \tag{34}$$

Similarly, we can measure the upside CoVaR as

$$\mathbb{P}\left(r_{i,\,t} \ge CoVaR^{U,\,i|j}_{\beta,\,1-\alpha,\,t} \middle| r_{j,\,t} \ge VaR^{j}_{1-\alpha,\,t}\right) = \beta \tag{35}$$

Based on the copula theory proposition, $F_j\left(VaR^{j}_{\alpha,\,t}\right) = \alpha$, so Equation (34) is equivalent to

$$\frac{\mathbb{P}\left(r_{i,\,t} \le CoVaR^{D,\,i|j}_{\beta,\,\alpha,\,t},\ r_{j,\,t} \le VaR^{j}_{\alpha,\,t}\right)}{\mathbb{P}\left(r_{j,\,t} \le VaR^{j}_{\alpha,\,t}\right)} = \frac{F_{i,\,j}\left(CoVaR^{D,\,i|j}_{\beta,\,\alpha,\,t},\ VaR^{j}_{\alpha,\,t}\right)}{F_j\left(VaR^{j}_{\alpha,\,t}\right)} = \beta \tag{36}$$

where $F_i(\cdot)$ and $F_j(\cdot)$ are the marginal distributions of *i* and *j* returns, respectively, and $F_{i,\,j}(\cdot)$ is their joint distribution function. Subsequently, we can measure the systematic impact of market *j*'s returns on market *i*'s returns by addressing Equations (37) and (38) in the following manner:

$$C\left(F_i\left(CoVaR^{D,\,i|j}_{\beta,\,\alpha,\,t}\right),\ F_j\left(VaR^{j}_{\alpha,\,t}\right)\right) = \alpha\beta \tag{37}$$

$$1 - F_i\left(CoVaR^{U,\,i|j}_{\beta,\,1-\alpha,\,t}\right) - F_j\left(VaR^{j}_{1-\alpha,\,t}\right) + C\left(F_i\left(CoVaR^{U,\,i|j}_{\beta,\,1-\alpha,\,t}\right), F_j\left(VaR^{j}_{1-\alpha,\,t}\right)\right) = \alpha\beta \tag{38}$$

where $C(\cdot)$ represents the dynamic t-copula of returns whose time-varying parameter is generated by the GAS process. Referring to Reboredo and Ugolini (2016), given the confidence levels α and β, $F_i\left(CoVaR^{i|j}_{\beta,\,\alpha,\,t}\right)$ can be obtained by inverting the copula function at time *t*. Then, $CoVaR^{i|j}_{\beta,\,\alpha,\,t}$ can be obtained through the inverse of the marginal function of $r_{i,\,t}$, namely $F_i^{-1}\left(F_i\left(CoVaR^{i|j}_{\beta,\,\alpha,\,t}\right)\right)$.

Additionally, since *CoVaR* cannot reflect the volatility scale of different markets, Δ*CoVaR* is further introduced to measure the risk contagion contribution. Similar to Girardi and Ergün (2013), the Δ*CoVaR* defined in Equation (39) is interpreted as the difference in *VaR* for *i* returns under extreme movement versus normal conditions of *j* returns. Further, we standardize Δ*CoVaR* to estimate %*CoVaR* using Equation (40), thus eliminating the magnitude effects and obtaining more accurate results reflecting risk spillover among paired markets.

$$\Delta CoVaR^{i|j}_{t} = CoVaR^{i|j}_{\beta,\,\alpha,\,t} - CoVaR^{i|j}_{\beta,\,0.5,\,t} \tag{39}$$

$$\%CoVaR^{i|j}_{t} = \frac{\Delta CoVaR^{i|j}_{t}}{CoVaR^{i|j}_{\beta,\,0.5,\,t}} \tag{40}$$

Based on above, the Kolmogorov–Smirnov (KS) test proposed by Abadie (2002) is employed to explore the possible reduction in downside and upside risk spillover effects. The KS test quantifies disparities between two cumulative quantile functions using the empirical distribution function, disregarding any underlying distribution functions, and is given as

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x|G_m(x) - H_n(x)| \tag{41}$$

where $G_m(x)$ and $H_n(x)$ denote the cumulative distribution functions of two time series, whose sample sizes are m and n, respectively. This paper tests the null hypothesis that there are no significant differences in strength regarding risk spillover with and without ESG integration, which is defined as

$$H_0: \ \%CoVaR_t^{i|j,\ ESG} = \%CoVaR_t^{i|j,\ NESG} \tag{42}$$

4. Data

To measure the performance of tech stocks regarding I4.0, the S&P Kensho New Economy Sector Indices, widely employed in the literature (Ghaemi Asl et al. 2023a; Liu 2024; Shrestha et al. 2023; Yaqoob and Maqsood 2024), are utilized as proxies for ten tech sectors. Following Liu et al. (2023), we use the S&P 500 ESG Index to represent the performance of ESG integration and the S&P 500 to represent those without special consideration of ESG. Table 1 presents a summary of the aforementioned indices. The data cover the period from June 2017 to October 2023 and are obtained from www.spglobal.com/spdji/ (accessed on 10 December 2023). All data are converted into logarithmic percentage returns as $r_t = ln(P_t/P_{t-1}) \times 100$. R programming is employed to execute computational tasks, and the main packages used are presented in Table A2.

Table 1. Summary of variables.

Variables	Abbr.	Details
S&P Kensho Human Evolution Index	HE	genetic engineering, wearables and virtual reality, nanotechnology and robotics, and 3D printing
S&P Kensho Democratized Banking Index	DB	alternative finance, future payments, and distributed ledger
S&P Kensho Final Frontiers Index	FF	deep-space and deep-sea exploration and development
S&P Kensho Intelligent Infrastructure Index	II	smart grids, smart buildings, sensors, and intelligent meters
S&P Kensho Smart Transportation Index	ST	autonomous vehicles, electric vehicles, and advanced transport systems
S&P Kensho Clean Power Index	CP	clean energy and cleantech
S&P Kensho Future Security Index	FS	cyber security, smart borders, robotics, drones, space, wearables, and virtual reality
S&P Kensho Future Communication Index	FC	digital communities, enterprise collaboration, and virtual reality
S&P Kensho Advanced Manufacturing Index	AM	smart factories, 3D printing, robotic, and virtual reality
S&P Kensho Sustainable Staples Index	SS	output enhancement, reducing waste, and minimizing resource exhaustion
S&P 500 Index	NESG	ESG factors are not considered during decision-making
S&P 500 ESG Index	ESG	ESG factors are considered during decision-making

Table 2 reports the descriptive statistics for all return series. All return series are stationary, exhibit non-normal distribution, and demonstrate autocorrelation and heteroscedasticity effects. In comparison to general stocks, ESG stocks exhibit higher mean values and greater standard deviation. The correlation matrix in Table 3 indicates high dependence within tech sectors, which validates the first hypothesis. The pairwise joint distributions of stock indices and tech sectors are plotted in Figure 1. All joint probability distributions manifest elliptical contours, exhibiting varying degrees of elongation and distortion, alongside approximately central symmetry with stronger tails in the lower left and upper right, and weaker tails in the upper left and lower right. However, a few joint distributions exhibit slightly heavier lower tails, indicating a higher likelihood of downside financial contagion. Moreover, nonlinear relationships observed in the scatters, particularly in the upper and lower tails, indicate the necessity of employing a nonlinear model to analyze risk spillover effects. These findings support the suitability of t-copula estimation for further investigation.

Figure 1. Pairwise joint probability distributions of stock indices and tech sectors.

Table 2. Descriptive statistics.

	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J-B	ADF	L-B	ARCH	KS
HE	0.008	7.868	−14.987	2.045	−0.343	3.271	739.244 ***	−12.505 ***	37.008 ***	330.936 ***	0.969 ***
DB	0.008	10.313	−15.282	1.907	−0.537	5.391	1999.542 ***	−11.185 ***	58.423 ***	464.737 ***	0.992 ***
FF	0.032	9.768	−14.910	1.510	−0.947	12.934	11,305.937 ***	−11.675 ***	130.364 ***	686.102 ***	0.960 ***
II	0.008	11.152	−12.943	1.651	−0.555	8.243	4576.876 ***	−11.272 ***	132.873 ***	581.268 ***	0.958 ***
ST	0.012	11.023	−14.664	1.985	−0.541	5.086	1788.960 ***	−10.911 ***	70.277 ***	431.811 ***	0.946 ***
CP	0.051	11.874	−14.487	2.092	−0.419	6.068	2482.981 ***	−10.868 ***	64.599 ***	391.948 ***	0.991 ***
FS	0.040	8.630	−11.732	1.444	−0.760	8.416	4839.877 ***	−12.075 ***	123.266 ***	616.678 ***	0.963 ***
FC	0.048	9.931	−12.328	1.938	−0.296	2.560	456.878 ***	−12.897 ***	22.023 ***	293.565 ***	0.960 ***
AM	0.040	10.758	−11.026	1.851	−0.289	4.337	1266.912 ***	−11.312 ***	91.192 ***	447.321 ***	0.959 ***
SS	0.027	11.390	−13.907	1.861	−0.437	7.625	3898.037 ***	−10.505 ***	73.080 ***	438.980 ***	0.979 ***
NESG	0.036	8.968	−12.765	1.272	−0.822	14.714	14,503.890 ***	−11.353 ***	262.519 ***	625.674 ***	0.957 ***
ESG	0.041	9.146	−12.769	1.281	−0.781	14.389	13,861.534 ***	−11.439 ***	264.037 ***	616.733 ***	0.955 ***

Note: *** denotes statistical significance at 1% level.

Table 3. Kendall's τ matrix.

	HE	DB	FF	II	ST	CP	FS	FC	AM	SS	NESG	ESG
HE	1.000	0.502	0.411	0.493	0.495	0.449	0.514	0.527	0.519	0.496	0.465	0.457
DB	0.502	1.000	0.515	0.654	0.672	0.528	0.619	0.670	0.660	0.561	0.619	0.610
FF	0.411	0.515	1.000	0.630	0.557	0.461	0.682	0.437	0.584	0.570	0.591	0.566
II	0.493	0.654	0.630	1.000	0.736	0.576	0.674	0.570	0.715	0.620	0.658	0.638
ST	0.495	0.672	0.557	0.736	1.000	0.581	0.614	0.614	0.695	0.615	0.606	0.591
CP	0.449	0.528	0.461	0.576	0.581	1.000	0.504	0.496	0.530	0.519	0.474	0.463
FS	0.514	0.619	0.682	0.674	0.614	0.504	1.000	0.598	0.671	0.588	0.655	0.635
FC	0.527	0.670	0.437	0.570	0.614	0.496	0.598	1.000	0.636	0.505	0.557	0.551
AM	0.519	0.660	0.584	0.715	0.695	0.530	0.671	0.636	1.000	0.573	0.651	0.636
SS	0.496	0.561	0.570	0.620	0.615	0.519	0.588	0.505	0.573	1.000	0.535	0.518
NESG	0.465	0.619	0.591	0.658	0.606	0.474	0.655	0.557	0.651	0.535	1.000	0.950
ESG	0.457	0.610	0.566	0.638	0.591	0.463	0.635	0.551	0.636	0.518	0.950	1.000

5. Empirical Results

5.1. Marginal Distribution

Table 4 displays the results of estimated marginal ARMA-GJR-GARCH–skew-t models, with optimal lag parameters determined via BIC. Mean equations for different tech sector returns adhere to various ARMA(p,q) models, with most coefficients significant at the 1% level. In the variance equations, the majority of coefficients are significant at the 1% level, suggesting a high persistence of volatility. Moreover, the sum of ARCH and GARCH terms for each return series is approximately 1, providing further confirmation of this persistence. Additionally, asymmetry and degrees-of-freedom parameters indicate non-normal error terms, effectively characterized by distributions exhibiting asymmetries and fat tails. Specifically, the asymmetry coefficients for all return series are significantly positive at the 1% level, suggesting right-skewed fat tails. Table 4 additionally includes an examination of goodness-of-fit tests to assess the adequacy of the models. Remarkably, both the Q and Q^2 statistics do not reject the null hypothesis of no autocorrelation at the 10% significance level. Moreover, the results of the ARCH-LM test indicate no evidence of residual heteroskedasticity in the estimated marginal models, even when assessed at the 10% significance level. By comparing these outcomes with those detailed in Table 2, it can be concluded that the ARMA-GJR-GARCH–skew-t models effectively characterize the marginal distributions of the tech stock return series.

Table 4. Estimated results for marginal distribution models.

	HE	DB	FF	II	ST	CP	FS	FC	AM	SS	NESG	ESG
Panel A: Mean Equation												
ϕ_1	−1.564 ***	−0.887 ***	−1.169 ***	−1.644 ***	0.101 ***	−0.314 ***	−0.275 ***	1.960 ***	−0.275 ***	−1.236 ***	−1.862 ***	−1.863 ***
	(0.000)	(0.038)	(0.010)	(0.025)	(0.004)	(0.104)	(0.074)	(0.001)	(0.005)	(0.002)	(0.000)	(0.000)
ϕ_2	−1.614 ***	0.814 ***	−1.170 ***	−0.702 ***	−0.993 ***	−0.964 ***	−0.938 ***	−0.981 ***	−0.989 ***	−0.992 ***	−0.985 ***	−0.985 ***
	(0.000)	(0.069)	(0.015)	(0.080)	(0.003)	(0.051)	(0.011)	(0.001)	(0.004)	(0.005)	(0.001)	(0.001)
ϕ_3	−0.787 ***	0.914 ***	−0.889 ***					0.011 ***				
	(0.000)	(0.048)	(0.011)					(0.000)				
θ_1	1.511 ***	0.875 ***	1.188 ***	1.655 ***	−0.074 ***	0.295 ***	0.275 ***	−1.969 ***	0.274 ***	1.239 ***	1.853 ***	1.854
	(0.000)	(0.042)	(0.004)	(0.000)	(0.002)	(0.111)	(0.054)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
θ_2	1.577 ***	−0.806 ***	1.197 ***	0.736 ***	0.998 ***	0.967 ***	0.965 ***	0.980 ***	0.999 ***	1.000 ***	0.976 ***	0.975 ***
	(0.000)	(0.073)	(0.004)	(0.054)	(0.000)	(0.020)	(0.010)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
θ_3	0.739 ***	−0.888 ***	0.919 ***	0.040 ***	0.026 ***				0.003 **			
	(0.000)	(0.055)	(0.001)	(0.001)	(0.002)				(0.001)			
Panel B: Variance Equation												
ω	0.085 ***	0.031 ***	0.030 ***	0.022 ***	0.032 ***	0.020 ***	0.044 ***	0.086 ***	0.072 ***	0.031 **	0.025 ***	0.027 ***
	(0.008)	(0.010)	(0.010)	(0.008)	(0.012)	(0.005)	(0.012)	(0.010)	(0.022)	(0.013)	(0.006)	(0.006)
α	0.013	0.049 ***	0.031 **	0.046 ***	0.069 ***	0.063 ***	0.026 *	0.074 ***	0.050 ***	0.105 ***	0.035 *	0.028
	(0.009)	(0.018)	(0.016)	(0.015)	(0.017)	(0.008)	(0.014)	(0.022)	(0.018)	(0.021)	(0.020)	(0.020)
β	0.912 ***	0.879 ***	0.888 ***	0.876 ***	0.876 ***	0.917 ***	0.872 ***	0.860 ***	0.868 ***	0.872 ***	0.834 ***	0.837 ***
	(0.017)	(0.017)	(0.023)	(0.021)	(0.019)	(0.010)	(0.022)	(0.004)	(0.021)	(0.019)	(0.020)	(0.020)
γ	0.104 ***	0.136 ***	0.138 ***	0.151 ***	0.108 ***	0.039 **	0.160 ***	0.091 ***	0.133 ***	0.048 *	0.273 ***	0.278 ***
	(0.001)	(0.032)	(0.034)	(0.037)	(0.029)	(0.019)	(0.036)	(0.023)	(0.033)	(0.027)	(0.048)	(0.048)
η	0.915 ***	0.825 ***	0.838 ***	0.876 ***	0.877 ***	0.916 ***	0.788 ***	0.822 ***	0.887 ***	0.865 ***	0.810 ***	0.811 ***
	(0.033)	(0.030)	(0.029)	(0.031)	(0.031)	(0.029)	(0.034)	(0.029)	(0.032)	(0.030)	(0.029)	(0.030)
ν	11.946 ***	12.174 ***	7.898 ***	19.065 **	15.409 ***	8.133 ***	16.821 ***	15.904 ***	9.443 ***	8.591 ***	7.186 ***	7.097 ***
	(2.972)	(3.427)	(1.405)	(7.593)	(5.232)	(1.471)	(5.903)	(6.146)	(1.934)	(1.728)	(1.264)	(1.226)
Panel C: Diagnostic Tests												
Q	8.299	3.208	6.218	6.833	13.213	11.361	8.118	4.718	13.362	9.497	5.334	4.803
	[0.479]	[0.608]	[0.516]	[0.785]	[0.516]	[0.765]	[0.769]	[0.870]	[0.835]	[0.432]	[0.822]	[0.890]
Q^2	9.574	8.215	9.174	6.346	9.173	6.573	6.531	5.306	5.762	10.099	5.925	5.014
	[0.600]	[0.976]	[0.797]	[0.741]	[0.212]	[0.330]	[0.617]	[0.909]	[0.204]	[0.486]	[0.868]	[0.904]
ARCH	10.094	7.913	9.058	6.545	9.254	6.253	6.336	5.258	5.544	9.663	5.892	5.011
	[0.432]	[0.637]	[0.527]	[0.768]	[0.508]	[0.794]	[0.786]	[0.873]	[0.852]	[0.471]	[0.824]	[0.890]

Notes: The Ljung–Box test and ARCH-LM test are applied to assess the presence of serial correlation and ARCH effect in the standardized residual sequence for each marginal model, respectively. The standard errors of parameter estimates are enclosed in parentheses, and the *p*-values of test statistics are reported within square brackets. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

5.2. Dependence Structure within Tech Sectors

To comprehensively understand the dependence structure within tech sectors, this study employs R-, C-, and D-vine methods, leveraging their distinct features. The detailed specifications of the estimated vines are documented in Table 5 and the copula families for selection are listed in Table A3. The first trees of the dependence structure of tech sectors modeled using three vines are presented in Figure 2, respectively, along with the selected pairwise copula families and fitted Kendall's τ.

Based on the outcomes in Table 5, the most common pairwise copula families are either Student-t or SBB1, which are frequently observed when analyzing financial data. The dependence structure described by the R-vine allows for great flexibility. In the core framework of the R-vine model, the variables ST and II form a central star-like structure, connected by multiple edges with DB, SS, AM, FS, and CP. Additionally, ST forms a sequential path-like structure with DB, FC, and HE. These structural configurations underscore the importance of ST and II within the model, emphasizing their pivotal roles in capturing underlying dependencies and dynamics. In the C-vine structure, the root node selection is optimized to maximize the sum of pairwise dependencies. In this context, II is identified as the root node, underscoring its significant reliance on all other sectors within the C-vine. Notably, II, along with other technology sectors, exhibits moderate levels of connectivity. Specifically, it demonstrates the weakest connection with HE (*SBB1*(0.44)), while displaying the strongest linkage with ST (*t*(0.70)). This positioning underscores the crucial role of II in the intersectoral dynamics within the C-vine framework. The D-vine tree for the ten sector representatives is constructed by maximizing the dependence between adjacent nodes. Within this structure, ST, II, AM, and FS are tightly interconnected through the t-copula characterized by symmetric dependence. In contrast, HE and CP exhibit weaker associations with other sectors, positioned at both ends of the path trail.

Table 6 presents AIC, BIC, and log-likelihood for three estimated vine copula models. The C-vine exhibits the lowest values for both AIC and BIC, followed by the R-vine method. Furthermore, the log-likelihood suggests that the C-vine method provides the best fit to the data, whereas the D-vine method yields the lowest degree of fit. Subsequently, the Vuong test (Vuong 1989) and Clarke test (Clarke 2007) are employed to conduct pairwise comparisons of the vine structures. The Schwarz-corrected Clarke and Vuong statistics presented in Table 6 indicate that at the 1% significance level, both the R-vine and C-vine significantly outperform the D-vine. Furthermore, the Clarke statistic suggests the superiority of the C-vine structure over the R-vine at a 5% significance level. However, Vuong's statistic fails to confirm this, even at a 10% significance level. Nevertheless, through the information criteria, it becomes evident that the fitting of the C-vine model is superior to that of the R-vine model.

Interestingly, in our study, the C-vine copula model surpasses the R-vine and D-vine models in the tech sector context due to strong mutual correlations, which aligns with Hypothesis 1. Contrary to what previous studies have suggested, the R-vine structure, despite its greater flexibility, may not always be the optimal choice.

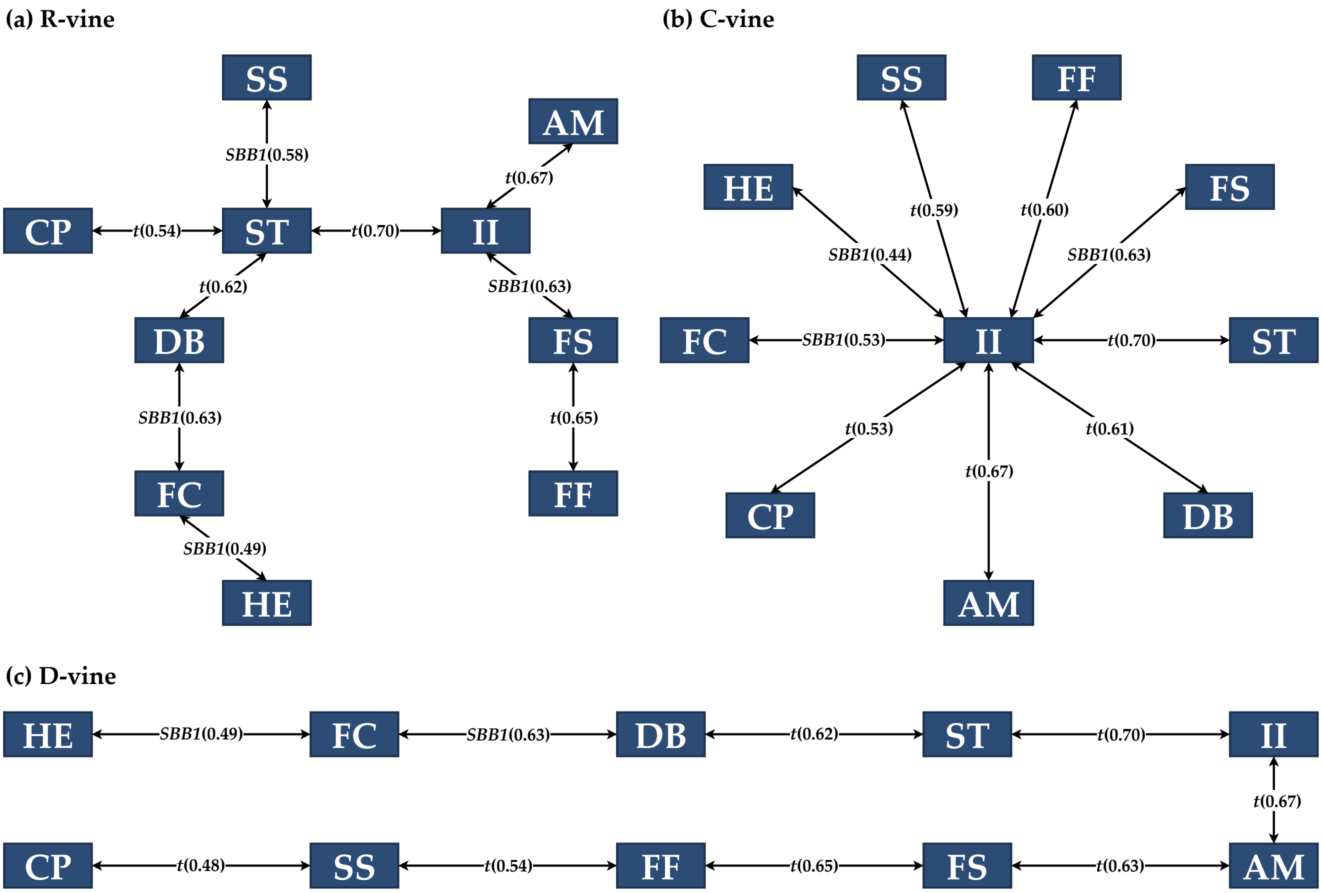

Figure 2. Estimated first-tree vine structures.

Table 5. Tree structures.

Tree	R-Vine							C-Vine							D-Vine						
	Edge	**Copula**	*par*	*par2*	τ	λ_u	λ_l	**Edge**	**Copula**	*par*	*par2*	τ	λ_u	λ_l	**Edge**	**Copula**	*par*	*par2*	τ	λ_u	λ_l
1	7,3	t	0.85	6.25	0.65	0.47	0.47	4,2	t	0.81	5.56	0.61	0.44	0.44	10,6	t	0.69	5.00	0.48	0.33	0.33
	4,7	SBB1	0.14	2.54	0.63	0.14	0.69	4,3	t	0.81	5.51	0.60	0.43	0.43	3,10	t	0.75	4.60	0.54	0.41	0.41
	4,9	t	0.87	5.59	0.67	0.53	0.53	4,6	t	0.74	6.55	0.53	0.32	0.32	7,3	t	0.85	6.25	0.65	0.47	0.47
	8,1	SBB1	0.13	1.82	0.49	0.06	0.54	4,1	SBB1	0.08	1.71	0.44	0.01	0.50	9,7	t	0.84	5.66	0.63	0.47	0.47
	2,8	SBB1	0.17	2.51	0.63	0.19	0.68	4,5	t	0.89	9.43	0.70	0.45	0.45	4,9	t	0.87	5.59	0.67	0.53	0.53
	5,2	t	0.83	6.29	0.62	0.44	0.44	4,7	SBB1	0.14	2.54	0.63	0.14	0.69	5,4	t	0.89	9.43	0.70	0.45	0.45
	5,6	t	0.75	6.90	0.54	0.32	0.32	4,9	t	0.87	5.59	0.67	0.53	0.53	2,5	t	0.83	6.29	0.62	0.44	0.44
	5,4	t	0.89	9.43	0.70	0.45	0.45	4,8	SBB1	0.19	1.93	0.53	0.15	0.57	8,2	SBB1	0.17	2.51	0.63	0.19	0.68
	10,5	SBB1	0.12	2.26	0.58	0.08	0.64	10,4	t	0.80	3.86	0.59	0.49	0.49	1,8	SBB1	0.13	1.82	0.49	0.06	0.54
2	4,3;7	t	0.30	6.12	0.19	0.09	0.09	8,2;4	SBB8	6.00	0.59	0.44	-	-	3,6;10	t	0.24	9.73	0.15	0.03	0.03
	9,7;4	F	2.68	0.00	0.28	-	-	8,3;4	t	0.02	18.95	0.01	0.00	0.00	7,10;3	F	2.67	0.00	0.28	-	-
	5,9;4	t	0.38	12.33	0.25	0.03	0.03	8,6;4	F	1.69	0.00	0.18	-	-	9,3;7	t	0.15	7.46	0.10	0.04	0.04
	2,1;8	SBB8	1.66	0.80	0.14	-	-	8,1;4	F	2.89	0.00	0.30	-	-	4,7;9	SBB1	0.07	1.32	0.27	0.00	0.31
	5,8;2	t	0.29	7.17	0.18	0.06	0.06	8,5;4	F	2.86	0.00	0.29	-	-	5,9;4	t	0.38	12.33	0.25	0.03	0.03
	4,2;5	t	0.30	5.96	0.19	0.09	0.09	8,7;4	t	0.46	15.87	0.30	0.02	0.02	2,4;5	t	0.30	5.96	0.19	0.09	0.09
	4,6;5	t	0.25	9.64	0.16	0.03	0.03	8,9;4	F	3.63	0.00	0.36	-	-	8,5;2	t	0.29	7.17	0.18	0.06	0.06
	10,4;5	SBB8	4.35	0.46	0.23	-	-	10,8;4	SBB8	2.66	0.58	0.18	-	-	1,2;8	SBB8	1.66	0.80	0.14	-	-
3	9,3;4,7	t	−0.03	11.65	−0.02	0.00	0.00	10,2;8,4	t	0.18	17.75	0.12	0.00	0.00	7,6;3,10	SBB8	2.02	0.66	0.14	-	-
	5,7;9,4	Tawn2_180	1.10	0.19	0.03	-	0.04	10,3;8,4	F	2.28	0.00	0.24	-	-	9,10;7,3	t	0.25	11.27	0.16	0.02	0.02
	2,9;5,4	SBB8	2.39	0.72	0.22	-	-	10,6;8,4	t	0.21	10.17	0.13	0.02	0.02	4,3;9,7	t	0.28	10.01	0.18	0.03	0.03
	5,1;2,8	t	0.18	11.15	0.11	0.01	0.01	10,1;8,4	t	0.27	11.39	0.18	0.02	0.02	5,7;4,9	SJ	1.05	0.00	0.03	-	0.07
	4,8;5,2	I	-	-	0.00	-	-	10,5;8,4	SG	1.21	0.00	0.17	-	0.23	2,9;5,4	SBB8	2.39	0.72	0.22	-	-
	10,2;4,5	t	0.16	27.83	0.10	0.00	0.00	10,7;8,4	F	1.60	0.00	0.17	-	-	8,4;2,5	I	-	-	0.00	-	-
	10,6;4,5	t	0.16	13.49	0.10	0.01	0.01	10,9;8,4	t	0.08	14.95	0.05	0.00	0.00	1,5;8,2	t	0.18	11.15	0.11	0.01	0.01
4	5,3;9,4,7	t	−0.02	21.36	−0.01	0.00	0.00	7,2;10,8,4	t	0.08	13.66	0.05	0.00	0.00	9,6;7,3,10	BB8	2.36	0.63	0.17	-	-
	2,7;5,9,4	t	0.25	10.70	0.16	0.02	0.02	7,3;10,8,4	t	0.56	8.51	0.38	0.14	0.14	4,10;9,7,3	t	0.27	11.02	0.18	0.02	0.02
	8,9;2,5,4	t	0.30	15.92	0.19	0.01	0.01	7,6;10,8,4	Tawn2_90	−1.15	0.08	−0.02	-	-	5,3;4,9,7	t	−0.02	20.56	−0.02	0.00	0.00
	4,1;5,2,8	BB8	1.39	0.79	0.08	-	-	7,1;10,8,4	SBB8	1.17	0.95	0.06	-	-	2,7;5,4,9	t	0.25	12.63	0.16	0.01	0.01
	10,8;4,5,2	t	0.04	30.00	0.02	0.00	0.00	7,5;10,8,4	t	−0.08	15.34	−0.05	0.00	0.00	8,9;2,5,4	t	0.30	15.92	0.19	0.01	0.01
	6,2;10,4,5	SG	1.06	0.00	0.05	-	0.07	9,7;10,8,4	t	0.20	13.18	0.13	0.01	0.01	1,4;8,2,5	BB8	1.39	0.79	0.08	-	-
5	2,3;5,9,4,7	t	−0.12	13.37	−0.08	0.00	0.00	5,2;7,10,8,4	t	0.20	10.30	0.13	0.02	0.02	4,6;9,7,3,10	t	0.23	10.14	0.15	0.02	0.02
	8,7;2,5,9,4	N	0.22	0.00	0.14	-	-	5,3;7,10,8,4	t	0.05	10.10	0.03	0.01	0.01	5,10;4,9,7,3	SBB8	3.61	0.51	0.22	-	-
	1,9;8,2,5,4	t	0.09	14.34	0.06	0.00	0.00	5,6;7,10,8,4	t	0.18	12.04	0.11	0.01	0.01	2,3;5,4,9,7	t	−0.12	13.09	−0.08	0.00	0.00
	10,1;4,5,2,8	SBB8	2.73	0.57	0.18	-	-	5,1;7,10,8,4	t	0.00	18.67	0.00	0.00	0.00	8,7;2,5,4,9	N	0.23	0.00	0.15	-	-
	6,8;10,4,5,2	F	0.69	0.00	0.08	-	-	9,5;7,10,8,4	t	0.22	16.36	0.14	0.00	0.00	1,9;8,2,5,4	t	0.09	14.34	0.06	0.00	0.00
6	8,3;2,5,9,4,7	t	−0.30	30.00	−0.19	0.00	0.00	1,2;5,7,10,8,4	I	-	-	0.00	-	-	5,6;4,9,7,3,10	t	0.20	12.35	0.13	0.01	0.01
	1,7;8,2,5,9,4	F	0.80	0.00	0.09	-	-	1,3;5,7,10,8,4	G90	−1.06	0.00	−0.06	-	-	2,10;5,4,9,7,3	t	0.10	30.00	0.06	0.00	0.00
	10,9;1,8,2,5,4	I	-	-	0.00	-	-	1,6;5,7,10,8,4	C	0.15	0.00	0.07	-	0.01	8,3;2,5,4,9,7	t	−0.30	30.00	−0.19	0.00	0.00
	6,1;10,4,5,2,8	C	0.13	0.00	0.06	-	0.01	9,1;5,7,10,8,4	SBB7	1.04	0.05	0.04	0.00	0.05	1,7;8,2,5,4,9	F	0.83	0.00	0.09	-	-
7	1,3;8,2,5,9,4,7	G90	−1.03	0.00	−0.03	-	-	9,2;1,5,7,10,8,4	t	0.07	13.38	0.05	0.00	0.00	2,6;5,4,9,7,3,10	N	0.06	0.00	0.04	-	-
	10,7;1,8,2,5,9,4	t	0.21	10.86	0.14	0.02	0.02	9,3;1,5,7,10,8,4	SG	1.07	0.00	0.06	-	0.09	8,10;2,5,4,9,7,3	SC	0.04	0.00	0.02	0.00	-
	6,9;10,1,8,2,5,4	t	−0.02	16.86	−0.01	0.00	0.00	9,6;1,5,7,10,8,4	t	−0.02	16.79	−0.01	0.00	0.00	1,3;8,2,5,4,9,7	G90	−1.03	0.00	−0.03	-	-
8	10,3;1,8,2,5,9,4,7	BB8	2.08	0.70	0.16	-	-	3,2;9,1,5,7,10,8,4	t	0.00	17.11	0.00	0.00	0.00	8,6;2,5,4,9,7,3,10	N	0.10	0.00	0.06	-	-
	6,7;10,1,8,2,5,9,4	Tawn270	−1.16	0.03	−0.01	-	-	6,3;9,1,5,7,10,8,4	Tawn2_180	1.77	0.01	0.01	-	0.01	1,10;8,2,5,4,9,7,3	t	0.22	12.69	0.14	0.01	0.01
9	6,3;10,1,8,2,5,9,4,7	Tawn2_180	2.07	0.01	0.01	-	0.01	6,2;3,9,1,5,7,10,8,4	I	-	-	0.00	-	-	1,6;8,2,5,4,9,7,3,10	C	0.12	0.00	0.06	-	0.00

Notes: *par* denotes the first parameter of the copula function and *par2* represents the second parameter if applicable. The edges are 1 = HE, 2 = DB, 3 = FF, 4 = II, 5 = ST, 6 = CP, 7 = FS, 8 = FC, 9 = AM, and 10 = SS.

Table 6. Model comparison for different vines.

Vine	AIC	BIC	Log-Likelihood	
R-vine	−19,164.33	−18,740.08	9661.17	
C-vine	−19,235.99	−18,827.85	9693.99	
D-vine	−19,085.19	−18,660.94	9621.59	
Combination	**Clarke Statistic**	**Clarke *p*-value**	**Vuong Statistic**	**Vuong *p*-value**
R-vine versus C-vine	750	0.029	−1.597	0.110
R-vine versus D-vine	852	0.004	2.992	0.003
C-vine versus D-vine	891	0.000	4.227	0.000

Notes: The tests proposed by Vuong (1989) and Clarke (2007) allow us to compare non-nested models. The Clarke and Vuong test statistics can be corrected for the number of parameters used in the models. The Schwarz-corrected statistics, which correspond to the penalty terms in the BIC, are reported.

5.3. Tech Sectors and Stock Market Dependence

This paper utilizes static t-copula estimation and conducts a goodness-of-fit test for bivariate copulas. Estimated parameters and dependence measures, along with the White test results, are reported in Table 7. The White test demonstrates that the t-copula effectively captures the relationship between stock indices and tech stocks. Figure 3 displays the estimated joint probability density of the bivariate variables, consistent with the contour plot in Figure 1. The distribution demonstrates heavy tails and symmetric centers, typical of a t-copula. This supports the appropriateness of utilizing a t-copula for modeling the joint distribution of the variables. However, in Figure 4, while all empirical lower tails remain within the 95% confidence interval of theoretical tail concentration, the upper tails fluctuate outside this interval. This suggests that the assumption of symmetric tail dependence in the t-copula hypothesis may not align with reality, which is common in financial data.

The results for the pairwise GAS t-copula are presented in Table 8, with the majority of coefficients found to be significant at a 1% confidence level. Figures 5 and 6 illustrate dynamic dependence, indicating a substantial rise during significant events such as the COVID-19 pandemic. Furthermore, various tech sectors display distinct and time-varying characteristics in their relationships with stock indices. The dynamic τ fluctuates around the static τ, indicating that the static τ can roughly describe pairwise dependence. However, as shown in Figure 6, certain dynamic tail dependencies, like HE, ST, CP, and FC, deviate notably from the static dependencies. Therefore, dynamic tail dependence might offer a more effective and accurate description of extreme events compared to static tail dependence.

Table 7. Estimated static bivariate t-copula and goodness-of-fit test.

	NESG					**ESG**				
	par	***par2***	τ	λ	**White Test**	***par***	***par2***	τ	λ	**White Test**
HE	0.61	8.10	0.42	0.17	9.321 ***	0.60	7.90	0.41	0.17	9.326 **
DB	0.79	5.43	0.58	0.42	17.256 ***	0.78	4.92	0.57	0.43	14.940 ***
FF	0.76	5.33	0.55	0.38	6.014 **	0.73	5.11	0.52	0.37	5.408 **
II	0.81	7.02	0.60	0.39	27.499 ***	0.79	6.35	0.58	0.39	25.310 ***
ST	0.77	11.63	0.56	0.23	9.645 **	0.76	9.62	0.55	0.25	9.980 ***
CP	0.63	7.77	0.44	0.19	21.782 ***	0.62	7.77	0.42	0.18	21.266 ***
FS	0.81	5.93	0.60	0.42	7.139 **	0.79	5.72	0.58	0.41	6.202 *
FC	0.74	8.51	0.53	0.26	16.644 ***	0.73	8.97	0.52	0.24	14.871 ***
AM	0.81	5.79	0.61	0.43	15.268 ***	0.80	5.42	0.59	0.43	15.603 ***
SS	0.70	5.97	0.50	0.31	23.543 ***	0.69	6.04	0.48	0.29	20.611 ***

Notes: The goodness-of-fit test uses the information matrix equality of White (1982) and was investigated by Huang and Prokhorov (2014). The null hypothesis is $H_0: H(\theta) + C(\theta) = 0$, where $H(\theta)$ is the expected Hessian matrix and $C(\theta)$ is the expected outer product of the score function. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

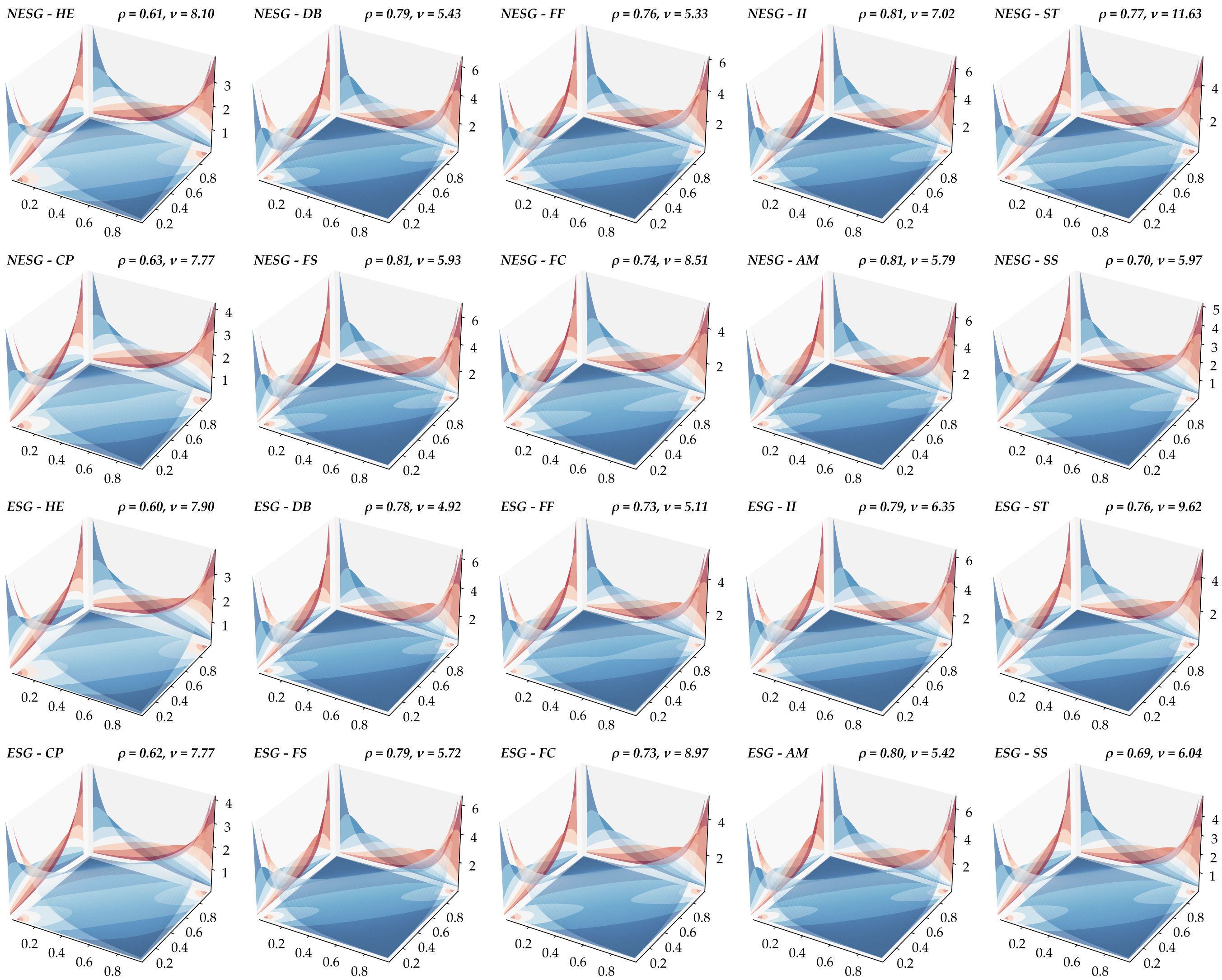

Figure 3. Pairwise joint probability densities of estimated static bivariate t-copula.

Table 9 further presents the average dependence measures of the dynamic t-copula. Kendall's τ assesses the overall relationship between general stock indices and tech sectors. The average τ between the general stock index and tech sectors ranges from 0.4179 (HE) to 0.5941 (II), indicating a moderate strength correlation. With ESG consideration, the range shifts to between 0.4101 (HE) and 0.5809 (AM), reflecting an overall decrease. The decrease in τ occurs in all ten sectors and varies across sectors, with the highest decrease in FS (3.77%) and the lowest in FC (1.23%). While Kendall's τ captures overall correlation, tail dependence examines extreme events in distribution tails. Despite similar τ values for the ten sectors, significant differences in tail dependence imply a diverse tail nature across sectors. When considering ESG, each sector's tail dependence on the stock index decreases to varying degrees. FS still experiences the most reduction (5.93%), and FC shows the least reduction (2.02%). Relative to the variability in Kendall's τ, the more pronounced variations in tail dependence signify heightened efficacy and advantages of ESG integration during extreme situations. The results of the KS test in Table 9 further demonstrate a significant difference in dependence between all ESG pairs and non-ESG pairs, which provides additional statistical evidence for our analysis.

In general, these empirical results provide evidence that ESG integration can reduce dependence between I4.0 tech sectors and the overall stock market and is consistent with Hypothesis 2.

Table 8. Estimated GAS t-copula models.

	HE	DB	FF	II	ST	CP	FS	FC	AM	SS
Panel A: NESG										
Ω	0.033 ***	0.037 ***	0.064 *	0.055 *	0.037 *	0.043 **	0.078 ***	0.028 ***	0.076 ***	0.035 ***
	(0.011)	(0.010)	(0.045)	(0.038)	(0.026)	(0.020)	(0.030)	(0.009)	(0.021)	(0.015)
A	0.019 ***	0.017 ***	0.017 ***	0.017 ***	0.017 ***	0.021 ***	0.017 ***	0.017 ***	0.017 ***	0.015 ***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)
B	0.965 ***	0.947 ***	0.914 ***	0.914 ***	0.947 ***	0.951 ***	0.881 ***	0.963 ***	0.881 ***	0.955 ***
	(0.012)	(0.014)	(0.061)	(0.058)	(0.039)	(0.022)	(0.045)	(0.011)	(0.032)	(0.019)
LL	−183.041	239.765	109.258	313.055	200.651	−155.064	274.662	91.767	312.497	−3.588
AIC	382.082	−459.529	−202.516	−606.109	−385.302	326.129	−529.324	−167.534	−604.995	23.177
BIC	425.043	−405.827	−159.555	−552.407	−342.340	369.091	−475.622	−124.572	−551.293	66.138
Panel B: ESG										
Ω	0.033 ***	0.026 ***	0.053 ***	0.046 *	0.038 ***	0.047 **	0.060 ***	0.028 ***	0.066 ***	0.030 **
	(0.012)	(0.006)	(0.021)	(0.029)	(0.013)	(0.023)	(0.024)	(0.011)	(0.023)	(0.017)
A	0.018 ***	0.017 ***	0.017 ***	0.017 ***	0.017 ***	0.023 ***	0.017 ***	0.017 ***	0.017 ***	0.014 ***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
B	0.964 ***	0.963 ***	0.930 ***	0.930 ***	0.947 ***	0.948 ***	0.914 ***	0.963 ***	0.900 ***	0.962 ***
	(0.012)	(0.008)	(0.028)	(0.043)	(0.018)	(0.025)	(0.034)	(0.014)	(0.034)	(0.021)
LL	−198.794	213.594	43.471	244.706	150.133	−181.933	204.400	70.139	257.416	−48.738
AIC	413.588	−411.188	−70.942	−469.412	−284.267	379.867	−392.800	−124.277	−498.832	113.475
BIC	456.549	−368.226	−27.981	−415.710	−241.305	422.829	−349.838	−81.315	−455.870	156.437

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 9. Average Kendall's τ and tail dependence.

	Kendall's τ				**Tail Dependence**			
	NESG	**ESG**	**Variation**	**KS Test**	**NESG**	**ESG**	**Variation**	**KS Test**
HE	0.418	0.410	1.85%	0.049 **	0.242	0.235	2.83%	0.049 **
DB	0.563	0.554	1.63%	0.069 ***	0.384	0.376	2.17%	0.069 ***
FF	0.538	0.520	3.40%	0.132 ***	0.354	0.336	5.22%	0.132 ***
II	0.594	0.577	2.94%	0.103 ***	0.417	0.398	4.63%	0.103 ***
ST	0.564	0.549	2.66%	0.081 ***	0.384	0.368	4.28%	0.081 ***
CP	0.435	0.421	3.17%	0.080 ***	0.256	0.244	4.49%	0.080 ***
FS	0.584	0.562	3.77%	0.157 ***	0.405	0.381	5.93%	0.157 ***
FC	0.516	0.510	1.23%	0.044 *	0.334	0.327	2.02%	0.044 *
AM	0.593	0.581	2.11%	0.103 ***	0.415	0.401	3.37%	0.103 ***
SS	0.503	0.485	3.58%	0.111 ***	0.318	0.301	5.49%	0.111 ***

Notes: The null hypothesis of the KS test conducted here is that the tail dependence of ESG-tech sectors and NESG-tech sectors are equal. The alternative hypothesis posits that the tail dependence of ESG-tech sectors is smaller than that of NESG-tech sectors. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

5.4. Tech Sector and Stock Market Spillover Effects

The findings in the preceding section highlight diverse dependencies among various tech sectors and the overall stock market, but they collectively form a broad spectrum of correlations, indicating a strong risk transmission effect.

Using the marginal model and t-copula, we calculate downside and upside *CoVaR* for stock indices (tech sectors) at a 95% confidence level (β = 0.05), conditioned on the *VaR* value of tech sectors (stock indices) at a 95% confidence level (α = 0.05). Then, the spillover effect measures Δ*CoVaR* and %*CoVaR* (Figures 7 and 8) are quantified. *CoVaR* exhibits temporal variations, with downside *CoVaR* consistently smaller than *VaR*, and upside *CoVaR* larger, indicating varying negative impacts on tech sectors (stock indices) during extreme risks in stock indices (tech sectors). Additionally, during the COVID-19 pandemic, risk spillover from tech sectors to stock indices surged significantly, while spillover from stock indices to tech sectors remained comparatively stable.

Tables 10 and 11 present average risk spillover and KS test statistics. It is evident that the magnitude of downside %*CoVaR* exceeds that of upside %*CoVaR* irrespective of the directional influence of spillover effects. In addition, there are significant differences between %*CoVaR* values of non-ESG pairs and those of ESG pairs in both downside and upside scenarios and the reduction is more pronounced for downside spillovers than upside spillovers, demonstrated by the KS tests. Hence, ESG integration can significantly reduce both downside and upside risk spillover between tech stocks and the overall stock market. Regarding downside risk, there is a greater reduction in spillover from tech sectors to stock indices compared to the reverse direction. Conversely, concerning upside risk, the reduction is less pronounced for spillover from tech sectors to stock indices compared to the reverse flow. In terms of specific sectors, FF and II show the greatest advantages of ESG integration. They benefit the most by receiving lower risks and contributing positively to risk transmission. This aligns with the strong connections seen earlier. However, the FC segment sees only minor reductions in risk and might even increase the transmission of upside risk to the overall stock market.

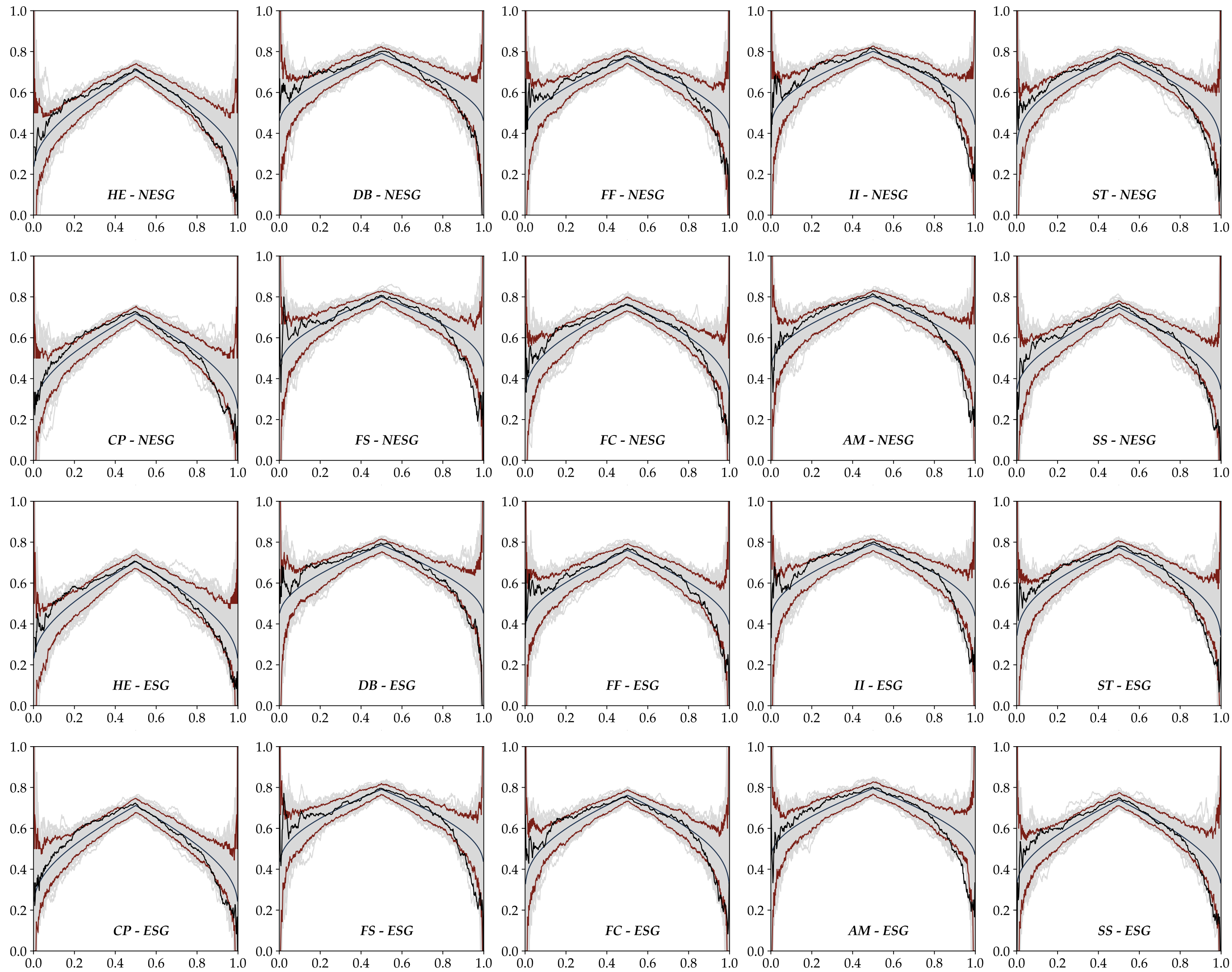

Figure 4. Tail concentrations of empirical and fitted static t-copulas. Notes: The dark blue and black lines are theoretical and empirical tail concentration functions, separately. The dark red lines represent 95% confidence intervals by bootstrapping. At a significance level of 10%, the results are considered acceptable.

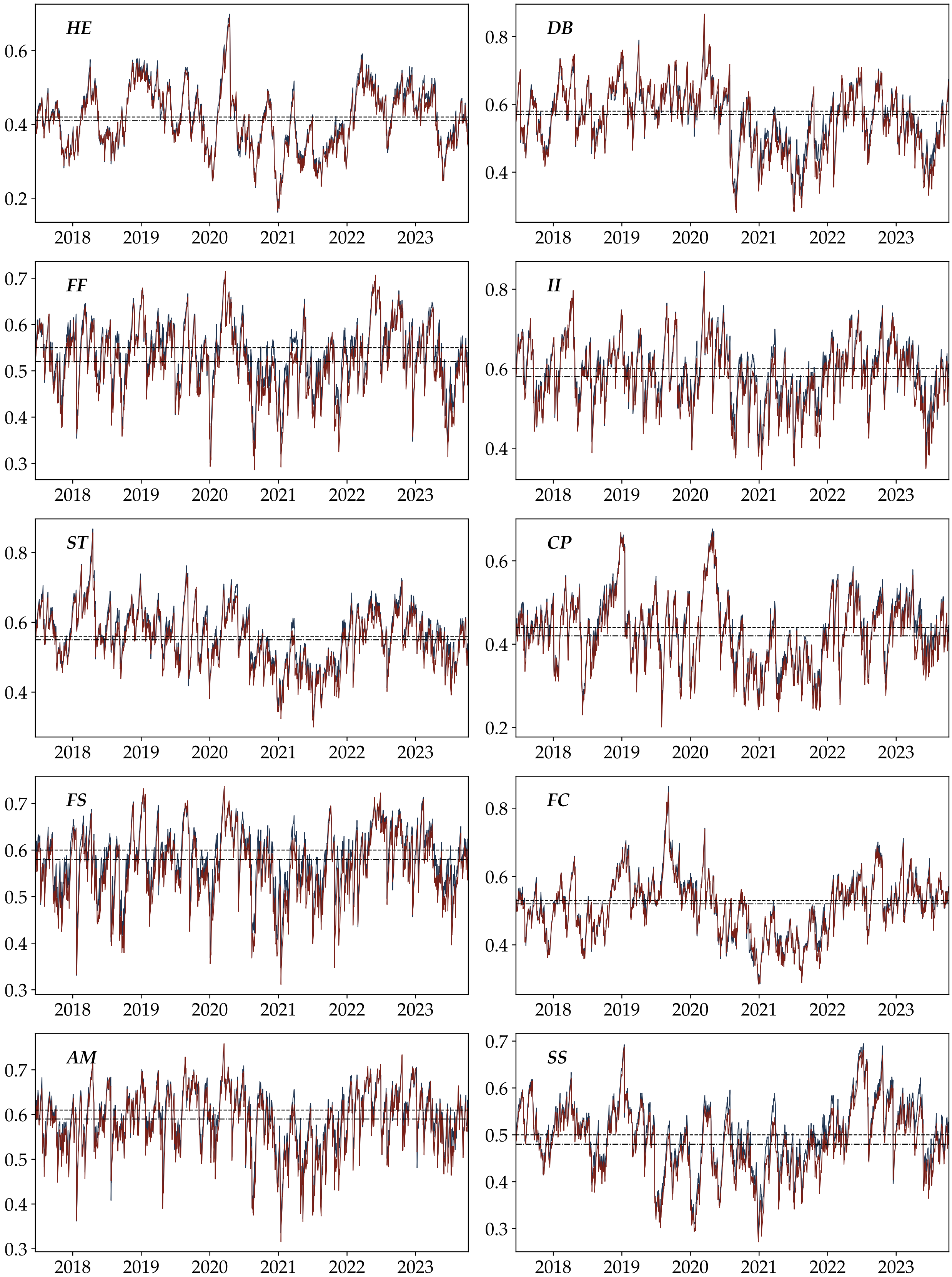

Figure 5. Time-varying Kendall's τ between tech sectors and the stock market. Notes: The dashed line and solid black line indicate static and dynamic cases where ESG is not considered. The dashed–dotted line and solid gold line denote static and dynamic cases where ESG is considered.

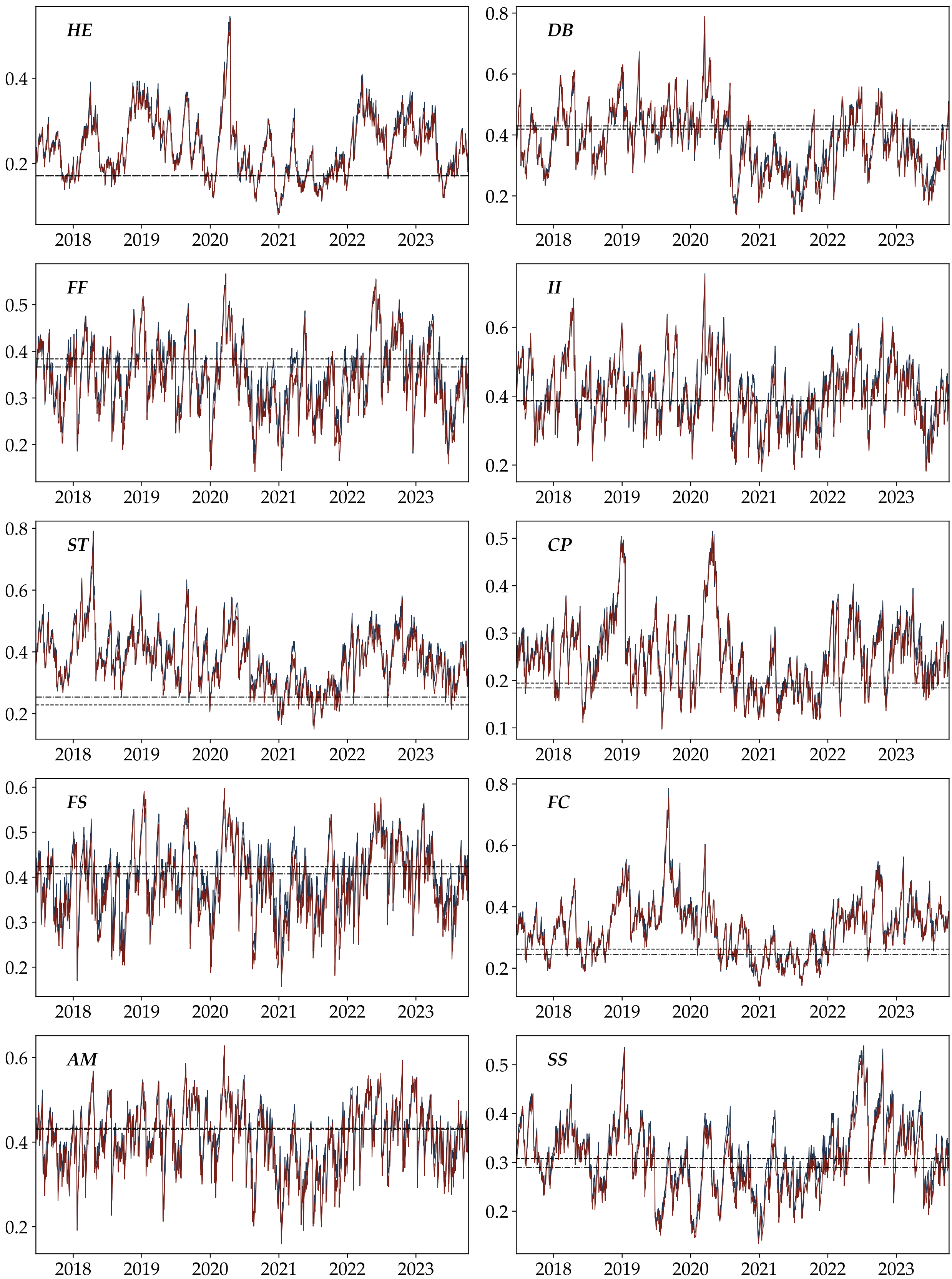

Figure 6. Time-varying tail dependence between tech sectors and the stock market. Note: see notes in Figure 5.

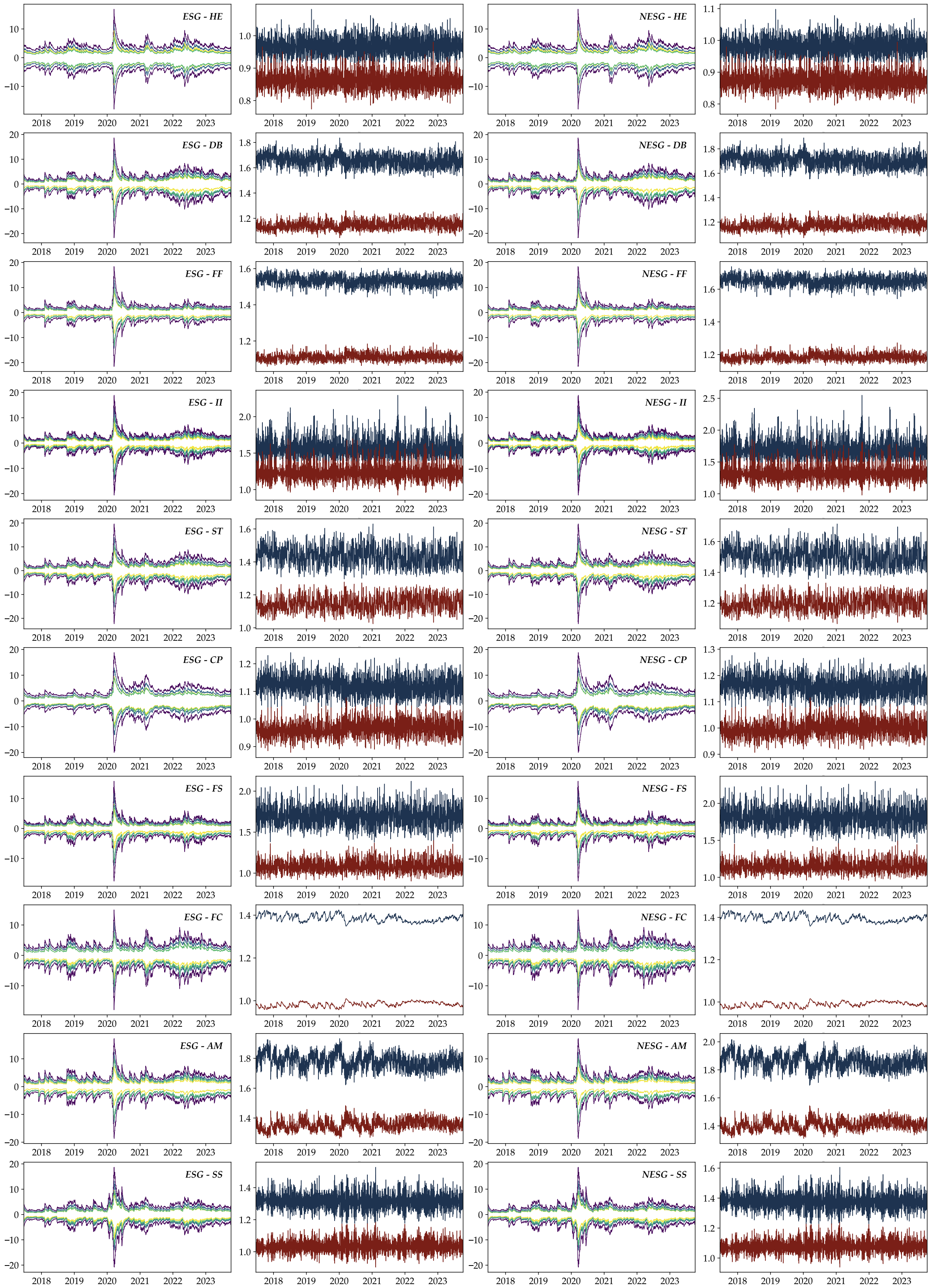

Figure 7. Risk spillover from stock indices to tech sectors. Notes: The blue lines represent the basic *VaR* of tech sectors, with pairwise *CoVaR* under extreme (indigo) and normal (yellow) conditions of the stock market, respectively. The green lines denote subsequent calculated Δ*CoVaR*, followed immediately to the right by the normalized downward (dark blue) and upward (dark red) %*CoVaR*.

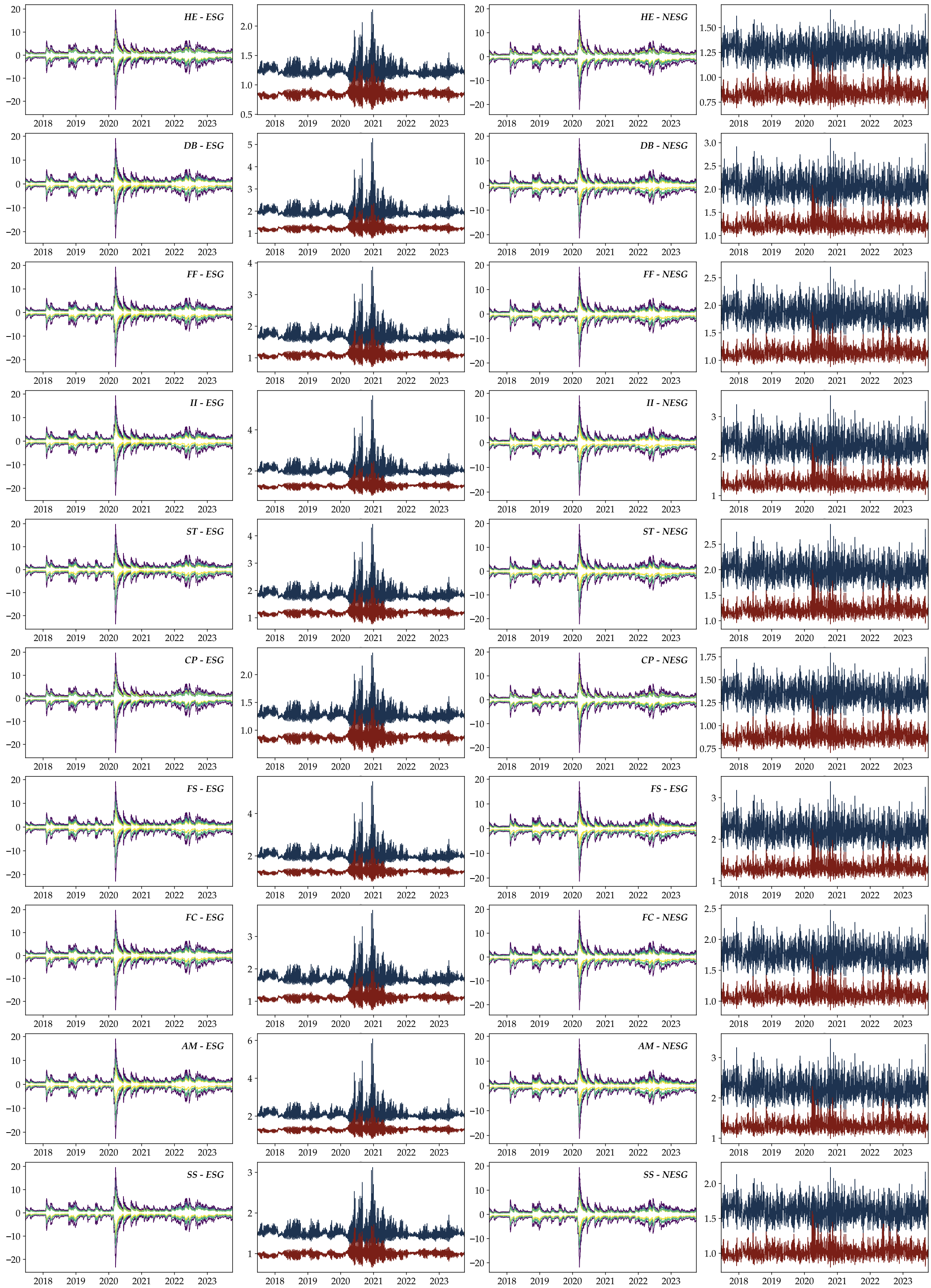

Figure 8. Risk spillover from tech sectors to stock indices. Notes: The blue lines represent the basic *VaR* of the stock markets, with pairwise *CoVaR* under extreme (indigo) and normal (yellow) conditions of the tech sectors, respectively. The green lines denote subsequent calculated Δ*CoVaR*, followed immediately to the right by the normalized downward (dark blue) and upward (dark red) %*CoVaR*.

Table 10. Risk spillover from stock indices to tech sectors.

	Downside			H_0: $\%CoVaR_t^{D,i\|j,NESG}$=$\%CoVaR_t^{D,i\|j,ESG}$	Upside			H_0: $\%CoVaR_t^{U,i\|j,NESG}$=$\%CoVaR_t^{U,i\|j,ESG}$
	NESG	ESG	Variation	H_1: $\%CoVaR_t^{D,i\|j,NESG}$>$\%CoVaR_t^{D,i\|j,ESG}$	NESG	ESG	Variation	H_1: $\%CoVaR_t^{U,i\|j,NESG}$>$\%CoVaR_t^{U,i\|j,ESG}$
HE	0.982	0.968	1.43%	0.171 ***	0.873	0.861	1.37%	0.157 ***
DB	1.705	1.658	2.76%	0.306 ***	1.174	1.146	2.39%	0.285 ***
FF	1.651	1.534	7.09%	0.953 ***	1.184	1.111	6.17%	0.908 ***
II	1.687	1.559	7.59%	0.287 ***	1.327	1.237	6.78%	0.259 ***
ST	1.503	1.434	4.59%	0.418 ***	1.199	1.149	4.17%	0.395 ***
CP	1.160	1.120	3.45%	0.382 ***	0.998	0.965	3.31%	0.365 ***
FS	1.811	1.691	6.63%	0.346 ***	1.147	1.085	5.41%	0.303 ***
FC	1.396	1.386	0.72%	0.225 ***	0.989	0.983	0.61%	0.198 ***
AM	1.860	1.781	4.25%	0.514 ***	1.407	1.355	3.70%	0.505 ***
SS	1.378	1.317	4.43%	0.362 ***	1.078	1.035	3.99%	0.336 ***

Notes: According to KS tests with the null hypothesis of $H_0: CoVaR_{\beta,\alpha,t}^{i|j} = CoVaR_{\beta,0.5,t}^{i|j}$, all risk spillovers are significant at the 1% confidence level (not shown). *** denotes statistical significance at the 1% level.

Table 11. Risk spillover from tech sectors to stock indices.

	Downside			H_0: $\%CoVaR_t^{D,j\|i,NESG}$=$\%CoVaR_t^{D,j\|i,ESG}$	Upside			H_0: $\%CoVaR_t^{U,j\|i,NESG}$=$\%CoVaR_t^{U,j\|i,ESG}$
	NESG	ESG	Variation	H_1: $\%CoVaR_t^{D,j\|i,NESG}$>$\%CoVaR_t^{D,j\|i,ESG}$	NESG	ESG	Variation	H_1: $\%CoVaR_t^{U,j\|i,NESG}$>$\%CoVaR_t^{U,j\|i,ESG}$
HE	1.270	1.246	1.89%	0.168 ***	0.846	0.845	0.12%	0.057 **
DB	2.055	1.993	3.02%	0.183 ***	1.241	1.229	0.97%	0.074 ***
FF	1.855	1.712	7.71%	0.349 ***	1.147	1.094	4.62%	0.210 ***
II	2.265	2.083	8.04%	0.325 ***	1.338	1.278	4.48%	0.191 ***
ST	1.979	1.879	5.05%	0.249 ***	1.218	1.187	2.55%	0.132 ***
CP	1.343	1.289	4.02%	0.243 ***	0.887	0.870	1.92%	0.119 ***
FS	2.198	2.047	6.87%	0.290 ***	1.307	1.258	3.75%	0.166 ***
FC	1.750	1.733	0.97%	0.125 ***	1.104	1.113	−0.82%	0.101 ***
AM	2.230	2.126	4.66%	0.221 ***	1.320	1.292	2.12%	0.110 ***
SS	1.603	1.522	5.05%	0.266 ***	1.024	0.997	2.64%	0.139 ***

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

The above findings align with Hypothesis 3. ESG integration can reduce dependence between the I4.0 tech sectors and the overall stock market.

6. Conclusions

This paper delves into the analysis of dependence structures within ten I4.0 tech stock sectors employing vine copula models. Subsequently, we employ a t-copula with a GAS process to characterize dynamic dependence, considering variations in the presence or absence of ESG considerations. Finally, the t-copula-based CoVaR approach is employed to comparatively assess spillover effects. The empirical results can be summarized as follows. Firstly, C-vine modeling demonstrates superior performance compared to the R-vine and D-vine in capturing interdependencies within the tech sector. Intelligent infrastructure, which relies significantly on smart transportation and advanced manufacturing, emerges as a crucial sector within tech sectors. Secondly, the integration of ESG considerations diminishes dependencies, particularly tail dependencies, between tech sectors and the stock market. Notably, this integration benefits the future security sector the most while offering relatively fewer benefits to the future communication sector. Thirdly, ESG integration effectively mitigates the transmission of risk spillovers between tech sectors and the stock market, notably impacting final frontiers and intelligent infrastructure. The reduction in downside spillovers is more pronounced than in upside scenarios, with downside risk spillovers from tech sectors to stocks experiencing a more significant decrease compared to the reverse direction in upside risk. Based on the aforementioned findings, it is evident that advocating ESG integration contributes to the establishment of a more stable financial market. This suggests a positive correlation between social development, environmental sustainability, and financial stability, indicating that they can be pursued simultaneously and mutually reinforce one another.

However, this paper may have limitations. Due to constraints in data availability, despite our comprehensive utilization of all of the Kensho Subsector Indices, there remains the possibility that certain sectors may not be fully represented. As the index family continues to evolve, it is foreseeable that additional tech subsector indices may become available in the future, thereby enhancing the breadth of our analysis. Moreover, in our examination of dependence and risk spillover, we have employed the symmetric t-copula to mitigate potential conflicts with distribution assumptions. However, given the diverse range of copula functions developed, there is ample scope for future research to explore the application of other copulas, particularly asymmetric copulas. Such endeavors would undoubtedly contribute to a more nuanced understanding of the dynamics at play within the technology sector and its interaction with broader financial markets.

The field of the association of social development, environmental sustainability, and financial stability offers ample opportunities for further exploration. Future research has the potential to thoroughly investigate the characteristics of individual technology-related stocks or specific tech companies, examining their stability in relation to ESG integration. Moreover, it is imperative to acknowledge the significance of different financial markets, encompassing bonds, commodities, currencies, digital financial assets, and others. Integrating comparisons with these alternative markets has the potential to augment the comprehensiveness of the analysis, thereby offering a more holistic perspective on the subject matter. Furthermore, given the disparities in technological development among different countries, conducting thorough comparative examinations is essential to understand the distinct characteristics of the technology sector in emerging countries compared to those in developed countries.

Author Contributions: Conceptualization, H.X. and J.C.; methodology, H.X.; software, H.X.; validation, H.X. and J.C.; formal analysis, H.X. and J.C.; investigation, H.X.; resources, P.Y.; data curation, J.C.; writing—original draft preparation, H.X. and J.C.; writing—review and editing, P.Y.; visualization, H.X.; supervision, P.Y.; project administration, P.Y.; funding acquisition, P.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The links for all data used in this article have been presented.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Methodological overview of relevant literature.

Authors	Marginals	Distributions	Copula Types	Dynamic Copula	CoVaR
Dai et al. (2023)	ARMA-GARCH	skew-t	Normal, Student-t, rotated Clayton, and rotated Gumbel copula	No	Yes
Hanif et al. (2022)	ARMA-TGARCH	skew-t	C-vine copula	ARMA(1,q) process	Yes
Jain and Maitra (2023)	AR-GARCH	(skew) normal, (skew) t, and (skew) GED	R-, C-, and D-vine copula	No	Yes
Kielmann et al. (2022)	ARMA-GARCH	normal and skew-t	D-vine copula	GAS	Yes
Rehman et al. (2023)	ARMA-GARCH	skew-t	Normal, Student-t, Frank, Plackett, rotated Gumbel, rotated Clayton, and SJC copula	ARMA(1,q) process	Yes
Yao and Li (2023)	ARMA-GARCH-MIDAS	normal	Student-t copula	GAS	Yes
Zeng et al. (2022)	AR-GJR-GARCH	skew-t	Vine copula, Student-t, and rotated 270 Clayton copula	No	Yes

Notes: The Marginals column denotes marginal distribution models, while the Distributions column indicates corresponding distribution assumptions for standardized residuals. The Copula Types column specifies the utilized copula (multiple copulas may be employed for the vine copula). The Dynamic Copula column indicates the incorporation of time-varying parameters and the generation process. The CoVaR column signifies the application of the CoVaR–copula approach.

Table A2. Main *R* packages and GitHub repositories.

R Package	Programmers
CDVineCopulaConditional	Bevacqua (2017)
copula	Hofert et al. (2023)
DistributionUtils	Scott (2018)
GAS	Ardia et al. (2019)
PerformanceAnalytics	Peterson and Carl (2020)
RCoVaRCopula *	Reboredo and Ugolini (2016)
rugarch	Ghalanos (2022)
stats	R Core Team (2023)
tseries	Trapletti and Hornik (2023)
TSP	Hahsler and Hornik (2023)
VineCopula	Nagler et al. (2023)

Notes: All packages are alphabetically sorted. * indicates a GitHub repository. Additional codes and necessary revisions are programmed by authors.

Table A3. Bivariate copula family set.

Copula Family	*par*	*par2*
Gaussian	$(-1, 1)$	-
Student-t	$(-1, 1)$	$(2, \infty)$
(Survival) Clayton	$(0, \infty)$	-
Rotated Clayton (90 and 270 degrees)	$(-\infty, 0)$	-
(Survival) Gumbel	$[1, \infty)$	-
Rotated Gumbel (90 and 270 degrees)	$(-\infty, -1]$	-
Frank	$R\backslash\{0\}$	-
(Survival) Joe	$(1, \infty)$	-
Rotated Joe (90 and 270 degrees)	$(-\infty, -1)$	-
(Survival) Clayton-Gumbel (BB1)	$(0, \infty)$	$[1, \infty)$
Rotated Clayton-Gumbel (90 and 270 degrees)	$(-\infty, 0)$	$(-\infty, -1]$
(Survival) Joe-Gumbel (BB6)	$[1, \infty)$	$[1, \infty)$
Rotated Joe-Gumbel (90 and 270 degrees)	$(-\infty, -1]$	$(-\infty, -1]$
(Survival) Joe-Clayton (BB7)	$[1, \infty)$	$(0, \infty)$
Rotated Joe-Clayton (90 and 270 degrees)	$(-\infty, -1]$	$(-\infty, 0)$
(Survival) Joe-Frank (BB8)	$[1, \infty)$	$(0, 1]$
Rotated Joe-Frank (90 and 270 degrees)	$(-\infty, -1]$	$[-1, 0)$
(Survival) Tawn type 1	$[1, \infty)$	$[0, 1]$
Rotated Tawn type 1 (90 and 270 degrees)	$(-\infty, -1]$	$[0, 1]$
(Survival) Tawn type 2	$[1, \infty)$	$[0, 1]$
Rotated Tawn type 2 (90 and 270 degrees)	$(-\infty, -1]$	$[0, 1]$

Notes: This table presents the copula family set from which bivariate copulas in vine copula models are selected. *par* denotes the first parameter of the copula function and *par2* represents the second parameter if applicable.

References

Aas, Kjersti, Claudia Czado, Arnoldo Frigessi, and Henrik Bakken. 2009. Pair-copula constructions of multiple dependence. *Insurance: Mathematics and Economics* 44: 182–98. [CrossRef]

Abadie, Alberto. 2002. Bootstrap Tests for Distributional Treatment Effects in Instrumental Variable Models. *Journal of the American Statistical Association* 97: 284–92. [CrossRef]

Adrian, Tobias, and Markus K. Brunnermeier. 2016. CoVaR. *American Economic Review* 106: 1705–41. [CrossRef]

Alkaraan, Fadi, Khaldoon Albitar, Khaled Hussainey, and V. G. Venkatesh. 2022. Corporate transformation toward Industry 4.0 and financial performance: The influence of environmental, social, and governance (ESG). *Technological Forecasting and Social Change* 175: 121423. [CrossRef]

Aloui, Riadh, Mohamed Safouane Ben Aïssa, and Duc Khuong Nguyen. 2011. Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking & Finance* 35: 130–41. [CrossRef]

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and David Gabauer. 2020. Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management* 13: 84. [CrossRef]

Ardia, David, Kris Boudt, and Leopoldo Catania. 2019. Generalized Autoregressive Score Models in R: The GAS Package. *Journal of Statistical Software* 88: 1–28. [CrossRef]

Arreola Hernandez, Jose, Shawkat Hammoudeh, Duc Khuong Nguyen, Mazin A. M. Al Janabi, and Juan Carlos Reboredo. 2017. Global financial crisis and dependence risk analysis of sector portfolios: A vine copula approach. *Applied Economics* 49: 2409–27. [CrossRef]

Ashfaq, Saleha, Yong Tang, and Rashid Maqbool. 2023. Insights of energy and its trade networking impacts on sustainable economic development. *Energy* 265: 126319. [CrossRef]

Asif, Muhammad, Cory Searcy, and Pavel Castka. 2023. ESG and Industry 5.0: The role of technologies in enhancing ESG disclosure. *Technological Forecasting and Social Change* 195: 122806. [CrossRef]

Aslam, Faheem, Ahmed Imran Hunjra, Elie Bouri, Khurrum Shahzad Mughal, and Mrestyal Khan. 2023. Dependence structure across equity sectors: Evidence from vine copulas. *Borsa Istanbul Review* 23: 184–202. [CrossRef]

Balcilar, Mehmet, David Gabauer, and Zaghum Umar. 2021. Crude Oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. *Resources Policy* 73: 102219. [CrossRef]

Baruník, Jozef, and Tomáš Křehlík. 2018. Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *Journal of Financial Econometrics* 16: 271–96. [CrossRef]

Bedford, Tim, and Roger M. Cooke. 2002. Vines–a new graphical model for dependent random variables. *The Annals of Statistics* 30: 1031–68. [CrossRef]

BenSaïda, Ahmed. 2023. The linkage between Bitcoin and foreign exchanges in developed and emerging markets. *Financial Innovation* 9: 38. [CrossRef] [PubMed]

BenSaïda, Ahmed, and Houda Litimi. 2021. Financial contagion across G10 stock markets: A study during major crises. *International Journal of Finance & Economics* 26: 4798–821. [CrossRef]

Bevacqua, Emanuele. 2017. CDVineCopulaConditional: Sampling from Conditional C- and D-Vine Copulas. Available online: https://CRAN.R-project.org/package=CDVineCopulaConditional (accessed on 16 March 2024).

Chen, Jiandong, Ming Gao, Sachin Kumar Mangla, Malin Song, and Jie Wen. 2020. Effects of technological changes on China's carbon emissions. *Technological Forecasting and Social Change* 153: 119938. [CrossRef]

Chen, Simin, Yu Song, and Peng Gao. 2023. Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *Journal of Environmental Management* 345: 118829. [CrossRef] [PubMed]

Clarke, Kevin A. 2007. A Simple Distribution-Free Test for Nonnested Model Selection. *Political Analysis* 15: 347–63. [CrossRef]

Creal, Drew, Siem Jan Koopman, and Andre Lucas. 2013. Generalized Autoregressive Score Models with Applications. *Journal of Applied Econometrics* 28: 777–95. [CrossRef]

Czado, Claudia. 2019. Analyzing dependent data with vine copulas. In *Lecture Notes in Statistics*. Berlin/Heidelberg: Springer, vol. 222.

Czado, Claudia, Eike Christian Brechmann, and Lutz Gruber. 2013. Selection of Vine Copulas. In *Copulae in Mathematical and Quantitative Finance*. Edited by P. Jaworski, F. Durante and W. K. Härdle. Berlin/Heidelberg: Springer, pp. 17–37.

Dai, Yun-Shi, Peng-Fei Dai, and Wei-Xing Zhou. 2023. Tail dependence structure and extreme risk spillover effects between the international agricultural futures and spot markets. *Journal of International Financial Markets, Institutions and Money* 88: 101820. [CrossRef]

Diebold, Francis X., and Kamil Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28: 57–66. [CrossRef]

Ding, Hao, Qiang Ji, Rufei Ma, and Pengxiang Zhai. 2022. High-carbon screening out: A DCC-MIDAS-climate policy risk method. *Finance Research Letters* 47: 102818. [CrossRef]

Dong, Xiyong, Youlin Xiong, Siyue Nie, and Seong-Min Yoon. 2023. Can bonds hedge stock market risks? Green bonds vs. conventional bonds. *Finance Research Letters* 52: 103367. [CrossRef]

Duan, Kun, Yanqi Zhao, Zhong Wang, and Yujia Chang. 2023. Asymmetric spillover from Bitcoin to green and traditional assets: A comparison with gold. *International Review of Economics & Finance* 88: 1397–417. [CrossRef]

Emir Hidayat, Sutan, Omar Bamahriz, Nadiah Hidayati, Citra Atrina Sari, and Ginanjar Dewandaru. 2022. Value drivers of startup valuation from venture capital equity-based investing: A global analysis with a focus on technological factors. *Borsa Istanbul Review* 22: 653–67. [CrossRef]

Forbes, Kristin J., and Roberto Rigobon. 2002. No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance* 57: 2223–61. [CrossRef]

Gao, Yang, Yangyang Li, Chengjie Zhao, and Yaojun Wang. 2022. Risk spillover analysis across worldwide ESG stock markets: New evidence from the frequency-domain. *The North American Journal of Economics and Finance* 59: 101619. [CrossRef]

Ghaemi Asl, Mahdi, Muhammad Mahdi Rashidi, Aviral Kumar Tiwari, Chi-Chuan Lee, and David Roubaud. 2023a. Green bond vs. Islamic bond: Which one is more environmentally friendly? *Journal of Environmental Management* 345: 118580. [CrossRef]

Ghaemi Asl, Mahdi, Oluwasegun B. Adekoya, and Muhammad Mahdi Rashidi. 2023b. Quantiles dependence and dynamic connectedness between distributed ledger technology and sectoral stocks: Enhancing the supply chain and investment decisions with digital platforms. *Annals of Operations Research* 327: 435–64. [CrossRef]

Ghalanos, Alexios. 2022. rugarch: Univariate GARCH Models. Available online: https://CRAN.R-project.org/package=rugarch (accessed on 16 March 2024).

Girardi, Giulio, and A. Tolga Ergün. 2013. Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance* 37: 3169–80. [CrossRef]

Hafner, Christian M., and Hans Manner. 2012. Dynamic stochastic copula models: Estimation, inference and applications. *Journal of Applied Econometrics* 27: 269–95. [CrossRef]

Hahsler, Michael, and Kurt Hornik. 2023. TSP: Traveling Salesperson Problem (TSP). Available online: https://CRAN.R-project.org/package=TSP (accessed on 16 March 2024).

Hanif, Waqas, Jose Areola Hernandez, Victor Troster, Sang Hoon Kang, and Seong-Min Yoon. 2022. Nonlinear dependence and spillovers between cryptocurrency and global/regional equity markets. *Pacific-Basin Finance Journal* 74: 101822. [CrossRef]

Hansen, Bruce E. 1994. Autoregressive Conditional Density Estimation. *International Economic Review* 35: 705–30. [CrossRef]

Hofert, Marius, Ivan Kojadinovic, Martin Maechler, and Jun Yan. 2023. copula: Multivariate Dependence with Copulas. Available online: https://CRAN.R-project.org/package=copula (accessed on 16 March 2024).

Hossain, Ashrafee T., Abdullah-Al Masum, and Jian Xu. 2023. COVID-19, a blessing in disguise for the Tech sector: Evidence from stock price crash risk. *Research in International Business and Finance* 65: 101938. [CrossRef]

Huang, Wanling, and Artem Prokhorov. 2014. A Goodness-of-fit Test for Copulas. *Econometric Reviews* 33: 751–71. [CrossRef]

Huang, Yingying, Kun Duan, and Andrew Urquhart. 2023. Time-varying dependence between Bitcoin and green financial assets: A comparison between pre- and post-COVID-19 periods. *Journal of International Financial Markets, Institutions and Money* 82: 101687. [CrossRef]

Jabbour, Charbel Jose Chiappetta, Ana Beatriz Lopes de Sousa Jabbour, Joseph Sarkis, and Moacir Godinho Filho. 2019. Unlocking the circular economy through new business models based on large-scale data: An integrative framework and research agenda. *Technological Forecasting and Social Change* 144: 546–52. [CrossRef]

Jain, Prachi, and Debasish Maitra. 2023. Risk implications of dependence in the commodities: A copula-based analysis. *Global Finance Journal* 57: 100859. [CrossRef]

Khan, Moin, Abid Haleem, and Mohd Javaid. 2023. Changes and improvements in Industry 5.0: A strategic approach to overcome the challenges of Industry 4.0. *Green Technologies and Sustainability* 1: 100020. [CrossRef]

Kielmann, Julia, Hans Manner, and Aleksey Min. 2022. Stock market returns and oil price shocks: A CoVaR analysis based on dynamic vine copula models. *Empirical Economics* 62: 1543–74. [CrossRef] [PubMed]

Koopman, Siem Jan, André Lucas, and Marcel Scharth. 2016. Predicting Time-Varying Parameters with Parameter-Driven and Observation-Driven Models. *The Review of Economics and Statistics* 98: 97–110. [CrossRef]

KPMG. 2022. *Mandatory ESG Reporting Is Here, and Finance Needs to Get Ready*. Amstelveen: KPMG. Available online: https://kpmg.com/uk/en/blogs/home/posts/2022/05/mandatory-esg-reporting.html (accessed on 8 February 2024).

Kumar, Mukesh, Rakesh D. Raut, Sachin Kumar Mangla, Soumyadeb Chowdhury, and Vikas Kumar Choubey. 2024. Moderating ESG compliance between industry 4.0 and green practices with green servitization: Examining its impact on green supply chain performance. *Technovation* 129: 102898. [CrossRef]

Liu, Jiexian. 2024. Analyzing the Co-movement of FinTech market efficiency and oil Resource efficiency: An Input-Output study. *Resources Policy* 90: 104668. [CrossRef]

Liu, Min, Tongji Guo, Weiying Ping, and Liangqing Luo. 2023. Sustainability and stability: Will ESG investment reduce the return and volatility spillover effects across the Chinese financial market? *Energy Economics* 121: 106674. [CrossRef]

Lourme, Alexandre, and Frantz Maurer. 2017. Testing the Gaussian and Student's t copulas in a risk management framework. *Economic Modelling* 67: 203–14. [CrossRef]

Maraqa, Basel, and Murad Bein. 2020. Dynamic Interrelationship and Volatility Spillover among Sustainability Stock Markets, Major European Conventional Indices, and International Crude Oil. *Sustainability* 12: 3908. [CrossRef]

Nagler, Thomas, Ulf Schepsmeier, Jakob Stoeber, Eike Christian Brechmann, Benedikt Graeler, and Tobias Erhardt. 2023. VineCopula: Statistical Inference of Vine Copulas. Available online: https://CRAN.R-project.org/package=VineCopula (accessed on 16 March 2024).

Nelsen, Roger B. 2006. Dependence. In *An Introduction to Copulas*. New York: Springer, pp. 157–225. [CrossRef]

Nguyen, Hoang, and Farrukh Javed. 2023. Dynamic relationship between Stock and Bond returns: A GAS MIDAS copula approach. *Journal of Empirical Finance* 73: 272–92. [CrossRef]

Ning, Cathy. 2010. Dependence structure between the equity market and the foreign exchange market–A copula approach. *Journal of International Money and Finance* 29: 743–59. [CrossRef]

Oh, Dong Hwan, and Andrew J. Patton. 2016. High-dimensional copula-based distributions with mixed frequency data. *Journal of Econometrics* 193: 349–66. [CrossRef]

Papathanasiou, Spyros, Ioannis Dokas, and Drosos Koutsokostas. 2022. Value investing versus other investment strategies: A volatility spillover approach and portfolio hedging strategies for investors. *The North American Journal of Economics and Finance* 62: 101764. [CrossRef]

Patton, Andrew J. 2006. Modelling Asymmetric Exchange Rate Dependence. *International Economic Review* 47: 527–56. [CrossRef]

Peterson, Brian G., and Peter Carl. 2020. Performance Analytics: Econometric Tools for Performance and Risk Analysis. Available online: https://CRAN.R-project.org/package=PerformanceAnalytics (accessed on 16 March 2024).

Pham, Linh, and Canh Phuc Nguyen. 2021. Asymmetric tail dependence between green bonds and other asset classes. *Global Finance Journal* 50: 100669. [CrossRef]

Rašiová, Barbara, and Peter Árendáš. 2023. Copula approach to market volatility and technology stocks dependence. *Finance Research Letters* 52: 103553. [CrossRef]

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing. Available online: https://www.R-project.org/ (accessed on 16 March 2024).

Reboredo, Juan C., and Andrea Ugolini. 2016. Quantile dependence of oil price movements and stock returns. *Energy Economics* 54: 33–49. [CrossRef]

Rehman, Mobeen Ur, Paraskevi Katsiampa, Rami Zeitun, and Xuan Vinh Vo. 2023. Conditional dependence structure and risk spillovers between Bitcoin and fiat currencies. *Emerging Markets Review* 55: 100966. [CrossRef]

Reischauer, Georg. 2018. Industry 4.0 as policy-driven discourse to institutionalize innovation systems in manufacturing. *Technological Forecasting and Social Change* 132: 26–33. [CrossRef]

Scott, David. 2018. DistributionUtils: Distribution Utilities. Available online: https://CRAN.R-project.org/package=DistributionUtils (accessed on 16 March 2024).

Shrestha, Keshab, Babak Naysary, and Sheena Sara Suresh Philip. 2023. Fintech market efficiency: A multifractal detrended fluctuation analysis. *Finance Research Letters* 54: 103775. [CrossRef]

Sklar, Martin J. 1959. Fonctions de Repartition a n Dimensions et leurs Marges. Available online: https://api.semanticscholar.org/CorpusID:127105744 (accessed on 16 March 2024).

Sukcharoen, Kunlapath, and David J. Leatham. 2017. Hedging downside risk of oil refineries: A vine copula approach. *Energy Economics* 66: 493–507. [CrossRef]

Tiwari, Aviral Kumar, Emmanuel Joel Aikins Abakah, Xuefeng Shao, TN-Lan Le, and Matthew Ntow Gyamfi. 2023. Financial technology stocks, green financial assets, and energy markets: A quantile causality and dependence analysis. *Energy Economics* 118: 106498. [CrossRef]

Trapletti, Adrian, and Kurt Hornik. 2023. tseries: Time Series Analysis and Computational Finance. Available online: https://CRAN.R-project.org/package=tseries (accessed on 16 March 2024).

Urom, Christian. 2023. Time–frequency dependence and connectedness between financial technology and green assets. *International Economics* 175: 139–57. [CrossRef]

Vuong, Quang. 1989. Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. *Econometrica* 57: 307–33. [CrossRef]

White, Halbert. 1982. Maximum Likelihood Estimation of Misspecified Models. *Econometrica* 50: 1–25. [CrossRef]

Xiao, Qin, Meilan Yan, and Dalu Zhang. 2023. Commodity market financialization, herding and signals: An asymmetric GARCH R-vine copula approach. *International Review of Financial Analysis* 89: 102743. [CrossRef]

Yao, Can-Zhong, and Min-Jian Li. 2023. GARCH-MIDAS-GAS-copula model for CoVaR and risk spillover in stock markets. *The North American Journal of Economics and Finance* 66: 101910. [CrossRef]

Yaqoob, Tanzeela, and Arfa Maqsood. 2024. The potency of time series outliers in volatile models: An empirical analysis of fintech, and mineral resources. *Resources Policy* 89: 104666. [CrossRef]

Yu, Poshan, Haoran Xu, and Jianing Chen. 2024. Double Asymmetric Impacts, Dynamic Correlations, and Risk Management Amidst Market Risks: A Comparative Study between the US and China. *Journal of Risk and Financial Management* 17: 99. [CrossRef]

Zeng, Hongjun, Abdullahi D. Ahmed, Ran Lu, and Ningjing Dai. 2022. Dependence and spillover among oil market, China's stock market and exchange rate: New evidence from the Vine-Copula-CoVaR and VAR-BEKK-GARCH frameworks. *Heliyon* 8: e11737. [CrossRef] [PubMed]

Zeng, Yongliang, Xiangfang Zhao, and Yiwen Zhu. 2023. Equity incentives and ESG performance: Evidence from China. *Finance Research Letters* 58: 104592. [CrossRef]

Zhang, Wenting, Xie He, and Shigeyuki Hamori. 2022a. Volatility spillover and investment strategies among sustainability-related financial indexes: Evidence from the DCC-GARCH-based dynamic connectedness and DCC-GARCH t-copula approach. *International Review of Financial Analysis* 83: 102223. [CrossRef]

Zhang, Xiaoke, Xuankai Zhao, and Yu He. 2022b. Does It Pay to Be Responsible? The Performance of ESG Investing in China. *Emerging Markets Finance and Trade* 58: 3048–75. [CrossRef]

Zheng, Yanting, Xin Luan, Xin Lu, and Jiaming Liu. 2023. A new view of risk contagion by decomposition of dependence structure: Empirical analysis of Sino-US stock markets. *International Review of Financial Analysis* 90: 102920. [CrossRef]