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ABSTRACT

The technology sector serves as a fundamental pillar for all industry sectors in the economy, playing a central role in driving worldwide economic growth. It particularly distinguishes itself in the U.S., representing approximately one-third of the global technology market. However, the technology sector is not a homogenous group of similarly focused companies, its industries vary significantly in their characteristics. This paper analyzes the relationships among U.S. technology industries defined by the Global Industry Classification Standard using Vine copulas and transfer entropy. It spans 1 January 2010–31 January 2024, to clarify intra-sectoral heterogeneity and identify key industries predicting the performance of others. Our findings highlight the predictive power of the semiconductor industry, with significant information transmission to all other industries. Contrarily, the flow in the opposite direction is significant in only 3 of 5 cases. The identification of semiconductors' central role is particularly valuable for both retail and institutional investors concentrating on technology stocks, as it may indicate future developments in the entire sector. Moreover, due to the industry's global importance, shocks in the semiconductor industry could propagate across the entire technology sector, leading to broader economic instability. Therefore, the semiconductor industry should be closely monitored by the policymakers too.

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1. Introduction

The technology sector currently stands as the primary catalyst for long-term economic growth and development, a position it is likely to maintain within the global economy for the foreseeable future (Maryska, Doucek, and Kunstova 2012; Xiang 2023). As a backbone for other industries, projections indicate that half of the global GDP is attributable to digitally transformed enterprises (Gens 2019). Companies that heavily invest in technological innovations not only enhance their economic performance and lower expenditures, but also maintain competitiveness in the digital business environment, outperforming industry peers in the stock market (Boasson and Boasson 2006; Brynjolfsson and Hitt 1994; Caldarelli, Ferri, and Maffei 2016; Ginesti et al. 2021; Lee 2005). The sector's pivotal role in supporting the economy also extends to market downturns, as seen in its positive growth rate during the recession in the latter half of the twentieth century or decoupling from the declining market manifested during the global financial crisis (Bekaert et al. 2012; Emsbo-Mattingly et al. 2017). Indeed, even in the recent COVID-19 pandemic, the technology sector was instrumental in broader stock market recovery (Mazur, Dang, and Vo 2023; Zaimovic and Dedovic 2021).

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It is particularly the U.S. market, where the technology sector emerges as one of the most strategically important advanced industries (Atkinson 2022). Its representation in the global technology market stands at nearly one third, which is 35% higher than the U.S. share of the overall global economy (Atkinson 2022). Noteworthy is the sector's robust performance, which accounted for over 10% of the nation's total GDP every year between 2020 and 2022 (Zippia 2023). Additionally, during the period spanning from 2013 to 2022, six distinct technology industries alone were responsible for driving 35% of the overall U.S. economic growth (Atkinson 2023). The sector's rising significance within the U.S. economy is further evidenced by its growing weight in stock market indices, nearly doubling in the benchmark S&P 500 index over the past two decades. Owing to its impressive performance, long-term investment in the U.S. technology sector has gained popularity, as it has delivered an annualised return nearly double that of the S&P 500 over the previous decade.

However, the technology sector is not a homogeneous group of companies. It encompasses distinct industries differing in key characteristics, which leads to varying behaviours on different occasions. Stocks of individual technology companies across various industries exhibit distinct patterns of co-movement and interdependence (Čeryová and Árendáš 2024). Their performance is influenced by numerous factors, including the stock exchange on which they are listed, which affects both performance and volatility (Bessembinder and Kaufman 2019). The benefits of ESG integration also vary across different segments of the technology sector (Yu, Xu, and Chen 2024). Such diversity in stock behaviour extends to market disruptions (Akhigbe, Larson, and Madura 2002). For example, during the COVID-19 pandemic, while most industries experienced declines, high-tech sectors demonstrated resilience (He et al. 2020). Similarly, during the Russia-Ukraine conflict, fintech-related segments of the technology sector showed lower volatility and higher returns compared to others (Hasan et al. 2023).

This paper explores the intricacies of the U.S. technology sector by analyzing the dependence and information transfer among its industries to clarify the documented intra-sectoral heterogeneity. Employing Vine copula modelling coupled with transfer entropy, we account for both linear and nonlinear relationships without imposing rigid assumptions on data. The Vine copula approach allows for the investigation of the tail dependence and asymmetry often observed in financial data. Paired with the quantification of the bidirectional information transmission among technology industries, we enhance the understanding of the intra-sectoral structure and the underlying causal relationships, which is crucial for technology-focused investors. To our knowledge, no previous study has employed this combination of methods.

Our findings demonstrate moderate to strong positive dependence among U.S. technology industries, with semiconductors as the central industry, validated by its growing global importance. The intra-sectoral relationships further intensify during periods of both lowest and highest returns, with increased co-movement being more prominent in market downturns. Additionally, we confirm noticeable heterogeneity in the dependence structure. Great asymmetry is also evident in bidirectional information transmission between the semiconductor industry and other technology industries. While semiconductors demonstrate predictive power over all of them, the information flow in the reverse direction is statistically significant in only 60% of cases.

The increasing significance of semiconductors documented in our findings, aligns with prior practitioner research, including Burkacky, Dragon, and Lehmann (2022) and Deloitte (2024). Since the semiconductor industry has predictive power over other technology industries, it is a key indicator for investors and portfolio managers to monitor, as its performance may indicate the broader direction of the technology sector. A timely identification of new developments can help industry practitioners make more informed asset allocation decisions. Moreover, by highlighting the industry's vulnerabilities, such as supply chain risks, and their impact on other industries, we encourage policymakers to implement measures promoting stability and growth within the technology sector, a key driver of global economic development in recent years. Academically, our work enhances the existing literature on intra-sectoral dependence and causality (Meric and Meric 1989; Meric, Ratner, and Meric 2008; Ratner and Leal 2005), especially in the context of the U.S. technology sector. However, earlier studies are limited by data from the 1970s to 2000s and methods that assume linearity or multivariate normality, which are questionable in financial data (Kan and Zhou 2006; Lee and McLachlan 2013). While the later research of Čeryová and Árendáš (2024) employs robust models without these restrictions, it focuses solely on the 7 large technology companies. After using current data, applying advanced methodologies, and analyzing the entire U.S. technology sector, our results offer a more comprehensive view of recent trends and provide a more accurate risk assessment. Thus, we provide a clearer understanding of the technology sector's dynamics and better inform both academic research and practical decision-making.

The remainder of this paper is organised as follows. The next section outlines the data and methodology, followed by the presentation of our results in section three. Two final sections provide the discussion and conclusion of the paper.

2. Materials and methods

To assess the dependencies and interactions among the U.S. technology industries, we examine the daily closing prices of all industry sub-indices of the S&P 500 benchmark stock market index, which are classified under the Information Technology sector according to the Global Industry Classification Standard (GICS). Details regarding the composition of the technology sector and its industries are available in Table A1 in the Appendix. In total, we evaluate six representatives of the technology industries: S&P 500 Software (Software), S&P 500 Technology Hardware (Hardware), S&P 500 IT Services (IT Services), S&P 500 Electronic Equipment, Instruments & Components, Storage & Peripherals (Electronic Equipment and Related), S&P 500 Communications Equipment (Communications Equipment), and S&P 500 Semiconductors & Semiconductor Equipment (Semiconductors).

The Software sub-index comprises companies primarily engaged in the development and distribution of software solutions, including industry giants such as Microsoft, Oracle, and Adobe. Conversely, the Hardware encompasses manufacturers of computing devices, microprocessors, graphic cards, servers, and related components. Leading companies in this sector include Apple, Hewlett Packard, and Western Digital. The IT Services sub-index features firms like IBM and Accenture, renowned for offering a wide array of software development and consulting services to clients. Furthermore, the Electronic Equipment and Related consists of companies such as Seagate, specialising in the production of electronic hardware and related peripherals. Communications Equipment focuses on manufacturers of communication network devices, represented by companies like Cisco Systems and Motorola Solutions. Lastly, the Semiconductors sub-index contains major semiconductor producers, including Qualcomm, AMD, and Intel, which are the main competitors in the semiconductor industry.

All data are collected from Yahoo Finance and MarketWatch platforms for the period spanning from 1 January 2010 to 31 January 2024. The time series of daily prices undergo a logarithmic transformation, with their descriptive statistics presented in Table A2 in the Appendix. To model the intra-sectoral dependence effectively, we utilise a range of copula functions across all three main Vine copula classes. Contingent on detecting significant dependence, we quantify the bidirectional information transfer among the technology industries using the concept of transfer entropy. These techniques, accounting for both linear and nonlinear dependencies, are shown to be superior to widely used statistical concepts such as Granger causality, Pearson correlation, or linear regression, which exhibit limitations due to their reliance on strict assumptions (Gencaga 2018; Jondeau and Rockinger 2006). To date, no prior study utilising this combination of methods has come to our attention.

For Vine copula modelling and transfer entropy to produce reliable results, data stationarity is required. Based on the results of the Phillips-Perron and KPSS unit root tests presented in Table A3, stationarity is implied. There is; however, an additional prerequisite of serial independence for the former, which is assessed using the Ljung–Box test detailed in Table A3. As autocorrelation is detected in all time series, an ARMA (m,n) model in combination with GARCH (1,1) is applied to produce a serially independent sample (Hofert et al. 2018). The optimal lag length for the ARMA process is determined using the AIC and BIC criteria[1], resulting in ARMA (0,1) for Hardware and Communications Equipment, ARMA (3,3) for Software, Semiconductors, and IT Services, and ARMA (5,4) for Electronic Equipment and Related. The GARCH (1,1) model is utilised thanks to its ability to provide accurate predictions despite its simplicity (Hansen and Lunde 2001). Within the GARCH process, Student-t innovations are employed to capture the leptokurtic tendencies in the distribution of financial returns (Arreola Hernandez et al. 2017).

As copulas are functions of uniform margins, the ARMA-GARCH standardised residuals are transformed into pseudo-observations, which are then fitted with a range of Vine copulas to determine the optimal model for the dependence structure among technology industries (Baillien, Gijbels, and Verhasselt 2022).

2.1. Vine copula models

Copulas are versatile mathematical functions which model a wide range of dependence structures by connecting multivariate distributions with their univariate margins, without imposing restrictions on the choice of marginals (Sklar 1959). Since the early 2000s, they have gained significant traction in the financial sector, particularly in risk management, portfolio optimisation and credit scoring (Bouyé et al. 2000; Haffar and Le Fur 2022).

However, standard copula models lack the flexibility needed to accurately capture multivariate dependence. They tend to become intricate in their structure, imposing limitations such as parameter restrictions (Brechmann and Schepsmeier 2013). In contrast, Vine copulas build up the dependence structure using pair copulas, allowing each pair to exhibit different strength and type of dependence (Nagler, Bumann, and Czado 2019). Such adaptable construction results in Vine copulas showing superiority over more complex models such as multiplicative Liebscher or Koehler-Symanowski copulas, as well as other models in multivariate settings such as nested Archimedean constructions and the DCC-GARCH model (Aas and Berg 2009; Fischer et al. 2009; Zhang et al. 2014).

Different classes of Vine copulas have garnered considerable popularity in prior financial research. For instance, Zhang, Zhang, and Lee (2022) utilise regular Vine (R-Vine) models, while Xu, Wei, and Cao (2017) employed drawable Vine (D-Vine) models, and Low et al. (2011) utilise canonical Vine (C-Vine) models. In contrast, our study examines all C-Vine, R-Vine, and D-Vine models to determine the dependence characteristics within the technology sector, enhancing the results' robustness.

The approximate inference of R-Vine copulas is provided in Cooke and Kurowicka (2006) as follows:

$$f(x_1, \ldots, x_n) = \left[\prod_{k=1}^{n} f_k(x_k)\right] \times \left[\prod_{i=1}^{n-1} \prod_{e \in E_i} c_{j(e),k(e)|D(e)}(F(x_{j(e)}|x_{D(e)}),\ F\,(x_{k(e)}|x_{D(e)}))\right]$$

where $f(x_1, \ldots, x_{\underline{n}})$ is the multivariate density, Fi represents the marginal distributions, $c_{j(e),k(e)|D(e)}$ denotes a bivariate conditional density copula with $j(e)$ and $k(e)$ as conditioned nodes and $D(e)$ as the conditioning set.

Being a subset of R-Vine models, C-Vines are recognisable for their star-like shape. As they are composed of trees, each tree nominates a root node chosen based on the criterion of having the highest absolute correlation with other variables. Consequently, they are recognised as a suitable choice to represent a multivariate dependence structure in which one key component exerts influence on the remaining ones (Czado, Brechmann, and Gruber 2013). In contrast, D-Vines promote linear tree shapes, meaning that the nodes in each tree cannot be linked to more than two edges. They provide a more accurate representation of dependence structures, in which a subset of variables with critical influence is identified (Min and Czado 2010).

To ascertain the best fitting Vine model illustrating the dependence structure within the U.S. technology sector, all three classes of Vine copulas are examined. Under each type, three specifications are considered: one allowing all available copula families (all), another supporting only Gaussian and Student-t copulas (tg), and a third limited to Gaussian copulas (g). The restriction to elliptical families is chosen for their higher computational efficiency and widespread use in regulatory bodies (Koziol, Schnell, and Eckhardt 2015; Yoshiba 2015). Vine copula parameters are estimated using the joint maximum likelihood (MLE) method. Its calculation for a simplified R-Vine copula is specified in Czado (2019)[2] as:

$$l_{log}(\theta; u) = \sum_{l=1}^{n} \sum_{m=1}^{d-1} \sum_{e \in E_m} log(c_{j_e,k_e|D_e}(C_{j_e|D_e}(u_{l,j_e}|u_{l,D_c}), C_{k_e|D_e}(u_{l,k_e}|u_{l,D_e}))).$$

where the observed data are represented by u, copula parameters by θ, e stands for an edge from the edge set E, and $C_{je|De}$ and $C_{ke|De}$ depend on pair copula parameters. The resulting models are evaluated on their AIC and BIC criteria.

Given that differences in evaluation criteria may be modest, we administer the Vuong test for competing copula models, assessing if two models provide equivalent fits for the underlying dataset or whether one model class is superior (Vuong 1989). It relies on the Kullback–Leibler criterion (KLIC) in the formulation of an asymptotic likelihood ratio test for the null hypothesis of equivalence between two model classes (Kullback and Leibler 1951):

$$\text{H0:KLIC(h0, f1, }\theta 1) = \text{KLIC(h0, f2, }\theta 2)$$

in which h0 represents the true unknown density, f1 and f2 approximate parametric densities, and θ1 and θ2 are parameters of compared models.

2.2. Transfer entropy

Transfer entropy is a versatile non-parametric model capable of capturing both linear and nonlinear dependencies in the quantification of information exchange. Specifically, it is liberated from the constraints of time series models when estimating dependence measures such as correlation, Granger causality, or information shares of Hasbrouck (1995). Moreover, as opposed to the method of Flad and Jung (2008), it does not build upon the assumption of cointegration, whose empirical support has been challenged in stock market research (Dimpfl and Peter 2013). By employing transfer entropy, it is possible to measure the transmission of information between data series using a model-free measure rooted in information theory.

Let's consider Z a stationary Markov process of order j. The probability of observing Z at time $t+1$ in state z conditional on previous j observations is defined as $p(z_{t+1}|z_t, \ldots, z_{t-j}+1) = p(z_{t+1}|z_t, \ldots, z_{t-j})$. In the bivariate case, the information flow from process Y to process Z is typically quantified by computing the deviation from the generalised Markov property, based on the Kullback–Leibler distance. Subsequently, the information transfer from Markov process Y to Z is specified in Schreiber (2000) as:

$$T_{Y \to Z}(k, j) = \sum_{Z,Y} p(z_{t+1}, z_t^{(j)}, y_t^{(k)}) \times log \frac{p(z_{t+1}|z_t^{(j)}, y_t^{(k)})}{p(z_{t+1}|z_t^{(j)})}$$

which emphasises that transfer entropy is an asymmetric metric, allowing for the assessment of the directionality by recognising the dominant information flow. In simpler terms, transfer entropy from Y to Z measures the supplementary information gained about the future value of Z from observing past values of Y, given that the history of Z is already known.[3]

3. Results

Estimated test statistics and the number of parameters for all Vine copula models are displayed in Table 1. The log-likelihood, AIC, and BIC criteria collectively identify the C-Vine model with

Table 1. Evaluation of the fitted Vine copula models with parameters estimated using the joint MLE method (all: all implemented pair copula models used, tg: only Student-t and Gaussian copula models used, g: only Gaussian copula models used).

Vine copula model	Log-likelihood	N-par	AIC	BIC
C-Vine-all	7802.88	28	−15549.76	−15376.93
R-Vine-all	7753.17	29	−15448.34	−15269.34
D- Vine-all	7770.99	28	−15485.98	−15313.15
C-Vine-tg	7760.30	30	−15460.60	−15275.43
R-Vine-tg	7745.50	30	−15431.00	−15245.83
D- Vine-tg	7743.57	30	−15427.15	−15241.97
R-Vine/C-Vine/D-Vine-g	7111.54	15	−14193.08	−14100.49

Source: Own elaboration.

unrestricted family parameter as the optimal choice. Following closely are the unrestricted D-Vine model and the C-Vine model consisting solely of Gaussian and Student-t pair copulas, which outperforms even the unrestricted R-Vine model. Subsequently, the remaining model specifications are comparably well suited to describe the dependence structure among technology industries, except for those constrained to the Gaussian copula only. The Gaussian family proves inadequate in capturing asymmetric relationships and tail behaviour, even in the highest correlations or other forms of co-dependencies. Its shortcomings in underestimating tail risk events have led to widespread criticism and attributions of blame for the global financial crisis (Puccetti and Scherer 2018). If not for this limitation, it would be a favourable candidate, being a simpler, streamlined model with roughly 50% fewer parameters to estimate.

As the variance in test statistics among various Vine classes is minimal in most cases, the test of Vuong (1989) is additionally employed to determine whether there is substantial evidence of superiority among examined models. Results presented in Table 2 reinforce the inferior performance of the Gaussian specification across all Vine classes. Contrarily, when the restriction is relaxed to both elliptical families, most models demonstrate comparable performance to the unrestricted specification. The inferior fit is only observed in the D-Vine case. Upon removal of all constraints, the D-Vine and R-Vine models are considered equivalent. As partial superiority of the unrestricted C-Vine model is identified, we adopt it since it was also chosen by all test statistics in Table 1.

The first tree of the unrestricted C-Vine specification is illustrated in Figure 1. The Semiconductors industry emerges as a key variable in defining the dependence structure within the U.S. technology sector. Manifesting the strongest relationships with remaining industries, it is chosen as a root node. Measured by Kendall's τ, the correlations are positive and material in all cases, ranging from 0.44 (with Hardware) to 0.54 (with Electronic Equipment and Related). Still, the dependence structure displays a level of heterogeneity. Semiconductors' relationship with the majority of industries, such as Hardware, IT Services and Software is best described by the bivariate Survival BB1 (SBB1) copula,

Table 2. Vuong model comparison test.

	Unadjusted		Akaike adjusted		Schwarz adjusted	
Comparison	Statistics	*p*-value	Statistics	*p*-value	Statistics	*p*-value
R-Vine-all vs. tg	0.51	0.61	0.57	0.57	11.56	0.44
R-Vine-all vs. g	12.69	0.00**	12.42	0.00**	2.84	0.00**
C-Vine-all vs. tg	1.76	0.08	1.85	0.06	12.05	0.04*
C-Vine-all vs. g	13.05	0.00**	12.81	0.00**	0.78	0.00**
D-Vine-all vs. tg	12.28	0.00**	11.88	0.00**	10.68	0.00**
D-Vine-all vs. g	13.02	0.00**	12.76	0.00**	2.23	0.00**
C-Vine-all vs. R-Vine-all	2.06	0.04*	2.10	0.04*	2.23	0.03*
C-Vine-all vs. D-Vine-all	1.30	0.19	1.30	0.19	1.30	0.19
R-Vine-all vs. D-Vine-all	−1.02	0.31	−1.07	0.28	2.10	0.21

Note: The unrestricted (all) model specification is compared with models where only Student-t and Gaussian copulas (tg) are allowed, and where the choice is limited to the Gaussian copula (g) only. The rejection of the null hypothesis at 1% level is marked ** and * at 5% level.

Source: Own elaboration.

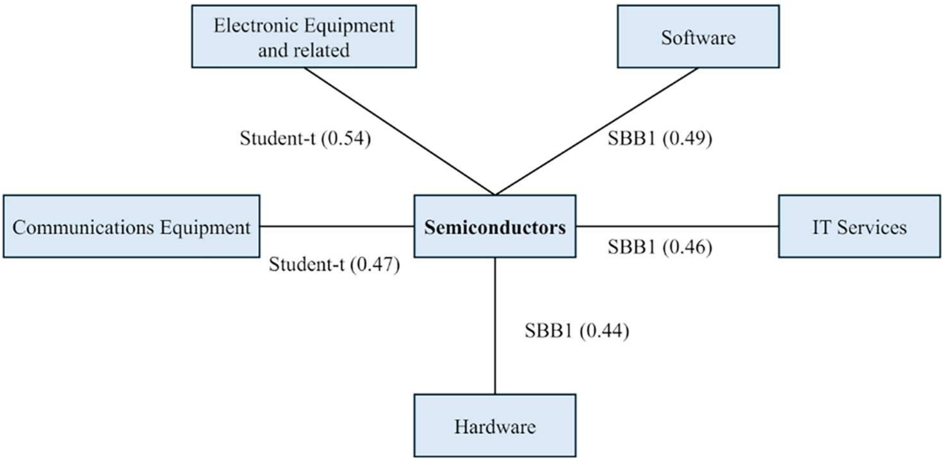

Figure 1. The first tree of the selected C-Vine structure together with chosen pair copula families and the corresponding fitted Kendall's τ values based on joint MLE.

Source: Own elaboration.

which portrays asymmetric dependence featuring tail risk with dominant lower tail. Hence, in times of crises or stock market contractions, co-movements between these pairs have an increasing tendency. On the other hand, the connection between Semiconductors and Communications Equipment, and Electronic Equipment and Related is characterised by the symmetric Student-t copula. Thus, their dependence with Semiconductors experiences symmetrical increases in times of both highest and lowest returns.

To further elaborate on the dependence heterogeneity, Table 3 reveals variations in the tail dependence featured in bivariate copulas with Semiconductors in the first tree. The highest upper tail dependence is estimated with Electronic Equipment and Related, indicating that this pair exhibits the highest likelihood of increased correlation in times of market prosperity. In contrast, the lowest upper tail coefficient is detected with Hardware, nearly five times smaller and approaching a negligible level. Conversely, the lower tail dependence appears to be more consistent across industries and generally higher, due to the usage of the SBB1 copula which emphasises this aspect. In particular, the biggest lower tail dependence is observed with Software, although it

Table 3. Joint MLE parameter estimates (θ and the second parameter), implied Kendall's τ, upper tail dependence (utd) and lower tail dependence (ltd) coefficients for the unrestricted C-Vine copula (abbreviations in the second column: 1 ↔ Hardware, 2 ↔ Software, 3 ↔ Electronic Equipment and Related, 4 ↔ Semiconductors, 5 ↔ IT Services, 6 ↔ Communications Equipment).

C-Vine tree	Edge	Copula	Parameter θ	Parameter 2	Kendall's τ	utd	ltd
1	6,4	Student-t	0.67	4.88	0.47	0.32	0.32
1	4,5	SBB1	0.27	1.63	0.46	0.21	0.47
1	4,3	Student-t	0.75	5.14	0.54	0.39	0.39
1	4,1	SBB1	0.16	1.65	0.44	0.08	0.48
1	4,2	SBB1	0.26	1.74	0.49	0.22	0.51
2	6,5;4	Frank	2.87	0.00	0.29	0.00	0.00
2	5,3;4	Student-t	0.46	9.16	0.30	0.08	0.08
2	5,1;4	BB8	6.00	0.31	0.21	0.00	0.00
2	5,2;4	SBB8	6.00	0.52	0.38	0.00	0.00
3	6,3;5,4	Frank	1.80	0.00	0.19	0.00	0.00
3	6,1;5,4	SBB8	1.77	0.74	0.13	0.00	0.00
3	6,2;5,4	Student-t	0.19	16.75	0.12	0.00	0.00
4	3,1;6,5,4	Student-t	0.07	21.76	0.04	0.00	0.00
4	1,2;6,5,4	Student-t	0.20	13.29	0.13	0.01	0.01
5	3,2;1,6,5,4	Student-t	−0.01	13.33	0.00	0.00	0.00

Source: Own elaboration.

is only 45% greater than the smallest, identified between the Semiconductors and Communications equipment.

Moving through the consecutive trees, the ordering of technology industries determined by the strength of their dependence is revealed. With Semiconductors as a root node exercising an influence on the remaining industries, the ranking of other nodes is as follows: IT Services, Communications Equipment, Hardware, Software and Electronic Equipment and Related. When the dependence is conditioned on stocks ranked by their relative significance in later trees, an intriguing pattern emerges: there is a consistent decline in Kendall's τ, accompanied by nearly complete disappearance of tail dependence. Its decline can be partially explained by the predominance of the Frank and BB8[4] copula families. The Frank family does not capture tail dependence, whereas the BB8 family does so only in a specific scenario, where its second parameter is set at 1; a constraint we did not impose (Cheng, Du, and Ji 2020).

The Vine copula analysis exposed a significant positive, yet heterogeneous dependence within the technology sector, with the Semiconductors industry holding a prominent role. To gain further insights into the industries' relationships with this key player, information transfer between Semiconductors and the remaining five industries is estimated in both directions and shown in Table 4. In general, the transmission of information from Semiconductors represents the dominant flow and demonstrates greater significance compared to the reverse direction. Specifically, the flux from Semiconductors is statistically significant across all cases, demonstrating its predictive power over the remaining industries. Even though its magnitude remains similar across almost all segments of the technology sector, the difference between the highest transfer and lowest transfer represents a nearly 50% reduction. The strongest transfer is observed to IT Services and the weakest to Hardware.

Conversely, the information flow from the five industries to Semiconductors is found to be statistically significant in only 60% of cases, with the largest information transfer observed from IT Services, and the smallest from Communications Equipment. Its strength demonstrates greater variability compared to the opposite direction. The information transfer is found insignificant in cases of Software and Electronic Equipment and Related. The lower proportion of material information transfer to Semiconductors suggests that the influence of other technology industries on Semiconductors may not be as direct or immediate. This asymmetry highlights its leading role and predictive power within the technology sector with its developments setting the course for all other technology industries.

Overall, the selection of Semiconductors as the most influential component within the U.S. technology sector is a natural consequence, considering their widespread usage (Xiang 2023). Serving as the building blocks of the entire electronics and computer industry, they are the lifeblood of the global economy and digital world (Jorgenson and Vu 2016; Wang and Chiu 2014). The implications from the transfer entropy estimation closely align with the inference drawn from the selection of the

Table 4. Transfer entropy estimation results from/to the Semiconductors industry to/from the other technology industries.

Industry X	Industry Y	Direction	Transfer entropy	*p*-value
Hardware	Semiconductors	X→Y	0.007	0.003**
Hardware	Semiconductors	Y→X	0.004	0.033*
Software	Semiconductors	X→Y	0.005	0.053
Software	Semiconductors	Y→X	0.006	0.003**
Electronic Equipment and Related	Semiconductors	X→Y	0.002	0.707
Electronic Equipment and Related	Semiconductors	Y→X	0.006	0.007**
IT Services	Semiconductors	X→Y	0.009	0.000
IT Services	Semiconductors	Y→X	0.006	0.003**
Communications Equipment	Semiconductors	X→Y	0.005	0.023*
Communications Equipment	Semiconductors	Y→X	0.006	0.007**

Significant transfer entropy at 1% level is denoted ** and * at 5% level.
Source: Own elaboration.

respective C-Vine copula model. The information transfer from Semiconductors, the root node, to other industries, is discovered to be stronger than in the opposite direction. The IT Services industry, which emerges as a leading player in bidirectional information transfer with Semiconductors, ranks second in the hierarchy of industry importance revealed by the C-Vine structure. In contrast, Software and Electronic Equipment and Related sectors, which demonstrate insignificant information transmission to Semiconductors, are positioned at the bottom of this ranking.

4. Discussion

The technology sector is anticipated to remain the driver for sustained economic development and serve as a catalyst for all other industries (Boasson and Boasson 2006; Maryska, Doucek, and Kunstova 2012; Mazur, Dang, and Vo 2023). Mainly in the U.S., it stands out for its growing importance, doubling its weight in the benchmark S&P 500 index over the past two decades. Moreover, the U.S. accounts for nearly one-third of the global technology industry (Atkinson 2022). In light of this, the current paper unravels the inner workings of the U.S. technology sector by analyzing the dependence and information flow among its six industries classified by the GICS.

We document moderate to strong positive dependence among the U.S technology industries, which exhibits an asymmetrically increasing tendency in times of highest and lowest returns, with a more pronounced effect observed in the latter. Semiconductors are identified as the key industry, exerting significant influence across all remaining industries despite the heterogeneous dependence structure. Additionally, we observe a significant asymmetrical bidirectional information transfer between Semiconductors and other industries, characterised by a dominant flow from Semiconductors, suggesting a certain degree of predictive power. In this direction, the information transmission is statistically significant across all industries, in contrast to a 60% significance level in the opposite direction. Transfer entropy results further validate the conclusions drawn from the Vine copula analysis: the highest bidirectional information transfer occurs with IT Services, an industry that ranks second in the hierarchy of importance. Conversely, negligible information flow is detected from industries positioned at the bottom of the hierarchy, namely Software and Electronic Equipment and Related.

5. Conclusion

The Semiconductors industry plays a pivotal role in the heterogeneous dependence within the technology sector, significantly influencing all its industries and demonstrating significant predictive power. Our findings suggest that intra-sectoral heterogeneity, documented by prior studies (Čeryová and Árendáš 2024; He et al. 2020), can stem from industry-specific differences. We additionally show that Semiconductors act as a central driver of information flow across the sector. The vital role of Semiconductors aligns with globalisation theories (Lamsal, Devkota, and Bhusal 2023), emphasising its global economic relevance. Nonetheless, recent years have exposed its vulnerabilities, such as the COVID-19-induced supply shortages, highlighting the limitations of supply chain resilience in globalised markets (Jorgenson and Vu 2016; Wang and Chiu 2014). These disruptions also affected traditional sectors, such as automotive and communications, causing broader economic impacts (Haramboure et al. 2023). Despite its challenges, the Semiconductors industry is expected to continue growing, with the global market projected to double to $1 trillion by 2030, driven in part by sustainability initiatives (Burkacky, Dragon, and Lehmann 2022; Deloitte 2024). However, significant challenges remain, including high capital costs, specialised labour needs, and reliance on East Asia for production, with Taiwan alone accounting for 92% of advanced capacity (Grimes and Du 2022; Varas et al. 2021). Although governments are taking steps to mitigate risks,[5] the impact of these measures will take time, making it essential for investors and analysts to account for industry-specific risks and monitor its developments closely.

Our research offers contributions that enhance both academic theory and practical decision-making. In terms of theory, we advance the literature on intra-sectoral dependence and causality within the technology sector. While earlier studies (Meric and Meric 1989; Ratner and Leal 2005) were limited by outdated data and assumptions of linearity, we utilise current data and advanced methodologies to capture more complex relationships. Unlike the focused scope of Čeryová and Árendáš (2024) on the largest 7 companies, our analysis covers the entire U.S. technology sector, providing a more accurate understanding of sector dynamics and risk. Future studies on sector patterns should consider industry-specific differences rather than treating sectors as homogenous. The practical implications of our results are particularly relevant for investors, portfolio managers, and policymakers. Given the Semiconductors industry's predictive power over other technology sectors, it serves as a critical indicator for market trends. Investors and portfolio managers should closely monitor its performance to inform asset allocation decisions, as shifts in the Semiconductors industry can signal broader movements within the technology sector. Additionally, the identification of increased correlations between technology stocks during market downturns highlights the need for risk mitigation strategies, such as hedging or portfolio diversification, to minimise potential losses. For policymakers, the vulnerabilities in the Semiconductors industry, particularly supply chain risks, require targeted support. Measures like tax incentives, research grants, and domestic production initiatives could help stabilise both the industry and the wider technology sector. Still, the presented findings have limitations, primarily due to the focus on the U.S., which may not fully represent global dynamics. The analysis, centred on six GICS industries, is static and may overlook evolving relationships and external factors. Future research could build on our study by incorporating global comparisons to assess how intra-sectoral relationships in the technology sector differ across regions. Additionally, applying dynamic models, such as regime-switching models, could provide insights into how the identified relationships change over time and under varying market conditions. Consequently, the understanding of the technology sector's dynamics and the broader economic implications of key industries like Semiconductors would be deepened.

Notes

1. Further details on the model specification are provided in Rašiová and Árendáš (2023).
2. Definitions of the likelihood for C-Vine and D-Vine models are available in Czado (2019).
3. Information transfer in the opposite direction is defined analogously.
4. As a mixture model of Frank and Joe copula models, the BB8 copula combines the strong positive dependence observed in Frank copulas with asymmetric tail dependence highlighted in Joe copula (Ehsan et al. 2020).
5. For example, the U.S. CHIPS and Science Act, the European Chips Act, and China's Made in China 2025 initiative.

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No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. The segmentation of the Information Technology GICS sector along with the tickers of the respective S&*P* 500 subindices (MSCI 2023).

Sector	Industry group	Industry
Information Technology (SP500-45)	Software & Services (SP500-4510)	IT Services (SP500-451020)
		Software (SP500-451030)
	Technology hardware & equipment (SP500-4520)	Communications Equipment (SP500-452010)
		Technology Hardware, Storage & Peripherals (SP500-452020)
		Electronic Equipment, Instruments & Components (SP500-452030)
	Semiconductors & semiconductor equipment (SP500-4530)	Semiconductors & semiconductor equipment (SP500-453010)

Source: Own elaboration based on MSCI (2023).

Table A2. Summary statistics of univariate log returns for January 1, 2010–January 31, 2024.

Index	Mean	St.Dev	Median	Min	Max	Range	Skew	Kurtosis
Hardware	0.0007	0.0165	0.0009	−0.1391	0.1089	0.2481	−0.2702	5.5895
Software	0.0007	0.0150	0.0009	−0.1506	0.1280	0.2786	−0.2917	7.3309
Electronic Equipment and Related	0.0003	0.0150	0.0006	−0.1317	0.0985	0.2301	−0.3473	5.4510
Semiconductors	0.0007	0.0179	0.0011	−0.1840	0.1188	0.3028	−0.3036	6.4489
IT Services	0.0005	0.0128	0.0010	−0.1428	0.1282	0.2711	−0.3028	11.8076
Communications Equipment	0.0003	0.0145	0.0005	−0.1103	0.1151	0.2254	0.5063	7.6916

Source: Own elaboration.

Table A3. Tests of stationarity and serial independence.

Index	PP test *p*-value	KPSS test *p*-value	Ljung Box test *p*-value
Hardware	<0.01	>0.1	0
Software	<0.01	>0.1	0
Electronic Equipment and Related	<0.01	>0.1	0
Semiconductors	<0.01	>0.1	0
IT Services	<0.01	>0.1	0
Communications Equipment	<0.01	>0.1	0

Note: Unit root tests results are presented in columns 2 and 3. Serial independence test results are presented in the last column.
Source: Own elaboration.