Connectedness Among Technology Stocks during Bear and Bull Market Phases

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Abstract:

This paper examines the spillover effects among main technology stocks (&P Kensho Artificial Intelligence (AI), S&P Kensho Cleantech (Cleantech), S&P Kensho Space (Space), S&P Kensho Smart Factories (Smart-Fact), S&P Kensho Enterprise Collaboration (Ent-Collabor), S&P Kensho Robotics (Robotics), S&P Kensho Autonomous Vehicles (Auto-Vehc), S&P Kensho Digital Communities (Dig-Comm), S&P Kensho Alternative Finance (Alt-Fin).) during bear and bull market modes and at both short and long terms. To do so, we use the relatively new quantile VAR model. The results show that the total spillover is dynamic and crisis sensitive. Moreover, the short-term spillover is stronger that the long-term spillover during bear, normal, and bull market scenarios. Furthermore, the short-term (long-term) spillover is higher during bull (bear) market conditions. AI and Smart-Fact stocks (Space stock) are (is) net shock receivers (transmitters) under different market scenarios and time horizons. For the remaining stocks, their role as a net shock receiver/transmitter is sensitive to the market modes and time investment horizons.

Keywords:

AI stocks, connectedness, time horizons, bear and bull market conditions.

1. Introduction:

The rapid employment of artificial intelligence (AI) technologies in diverse sectors of economic activity have catalyzed transformative changes across a wide spectrum of industries. The use of AI has enhanced the production process and reduced the costs (Gubareva et al., 2025; Huynh et al., 2020). COVID-19 pandemic has significantly contributed to the development of technology industry. For example, the profit margin of Alphabet, Amazon, Microsoft, OpenAI, NVIDI, and Meta companies, the leader technology companies in the globe, has increased significantly in the last few years. The evolution of AI stocks has influenced the dynamic of financial markets. The new stock class has attracted the attention of investors and portfolio managers.

The examination of connectedness among artificial intelligence (AI) and associated technology sectors has become increasingly pertinent in light of their expanding influence on global financial markets and economic development. From a theoretical perspective, this inquiry is grounded in several foundational financial and economic frameworks. Primarily, contagion theory posits that shocks emanating from one segment of a highly interconnected market can propagate swiftly to related sectors, thereby exacerbating systemic risk and potentially precipitating broader market instability. Given the accelerated integration and growing market capitalization of sectors such as AI, robotics, cleantech, autonomous vehicles, and digital communications, understanding the dynamics of risk transmission within this technology ecosystem is imperative. Furthermore, in accordance with portfolio diversification theory, the effectiveness of risk mitigation strategies hinges upon a rigorous understanding of the co-movement and spillover patterns among assets, particularly under varying market conditions. Analyzing connectedness across multiple technology subsectors provides critical insights into whether these assets contribute to true diversification benefits or exhibit heightened correlations that may undermine portfolio resilience, especially during periods of market stress.

Additionally, the distinctive characteristics of these sectors—marked by rapid innovation, technological disruption, and evolving investor perceptions—introduce complexities in risk behavior that challenge conventional modeling approaches. The notion of systemic risk underscores the necessity to investigate the temporal and state-dependent nature of spillovers to inform regulatory frameworks aimed at maintaining financial stability without stifling technological progress. Finally, considering the contemporary economic landscape characterized by geopolitical uncertainty, technological acceleration, and episodic crises such as the COVID-19 pandemic, a comprehensive analysis of connectedness within the broader technology domain is essential.

Recent empirical research has increasingly focused on the connectedness between artificial intelligence (AI) stocks and various asset classes, revealing complex interdependencies and varying risk transmission patterns across markets. For example, Gubareva et al. (2025) examined the interplay among AI, crude oil, clean energy, and conventional assets, finding AI and clean technology to be net transmitters of shocks, while oil and currency indices typically absorb shocks. Bas et al. (2024) explored the connectedness among technology stocks, cryptocurrencies, and non-fungible tokens (NFTs), reporting generally weak linkages that suggest diversification benefits across these emerging asset classes. Several studies have highlighted the importance of tail risk dynamics within AI-related markets. Ali et al. (2024) found that spillovers between Fin tech and AI stocks intensified sharply during the initial COVID-19 wave, with AI stocks acting as consistent shock transmitters. Jareño and Yousaf (2023) documented that connectedness between AI stocks and tokens strengthens notably during economic turbulence, particularly in the lower and upper quantiles, indicating heightened sensitivity to extreme market conditions. Yousaf et al. (2024) similarly identified moderate connectedness between AI tokens, AI ETFs, and other assets under normal conditions, but observed intensified spillovers during market extremes, limiting diversification benefits. Their findings also indicate that AI tokens may provide low-cost hedging opportunities for traditional assets, except for oil and cryptocurrencies. Beyond AI-specific markets, Yadav et al. (2024) studied the connectedness between major AI stocks (Microsoft, Google, Amazon, Meta, NVIDIA) and agricultural commodities during the COVID-19 pandemic and the Russia-Ukraine conflict. They identified Microsoft as both a major shock transmitter and receiver, while agricultural commodities like rice and corn showed limited shock transmission. Ha (2024) examined dynamic spillovers among robotics, AI ETFs, and carbon emission futures, finding that carbon futures absorb shocks while AI ETFs transmit them, with significant shifts in connectivity during major crises reflecting changes in investor sentiment and environmental market dynamics.

While these studies offer valuable insights into AI-related connectedness, the literature remains fragmented regarding the dynamic and extreme connectedness across a broad set of emerging technology sectors. In particular, the interplay between AI and other high-growth tech industries such as cleantech, robotics, smart factories, and alternative finance has been insufficiently explored. Additionally, few studies have examined connectedness patterns over a long-term horizon encompassing multiple global crises and market regimes.

To fill this gap, this study aims to assess the magnitude and direction of connectedness among major AI-driven technology sectors using nine thematic indices: S&P Kensho Artificial Intelligence (AI), Cleantech, Space, Smart Factories, Enterprise Collaboration, Robotics, Autonomous Vehicles, Digital Communities, and Alternative Finance. We employ the quantile frequency connectedness approach proposed by Chatziantoniou et al. (2022), which allows us to capture the dynamics of interconnectedness across different market conditions—specifically during extreme downside (bear) and upside (bull) regimes—and across heterogeneous investment horizons (short- and long-term). The dataset spans from March 13, 2018, to January 10, 2025, covering several key economic and geopolitical disruptions including the COVID-19 pandemic, the Russia–Ukraine war, U.S.–China trade tensions, the AI Safety Summit, and recent financial sector instabilities.

The results indicate that the spillover is strong at the short term than the long term during the normal market scenario. Connectedness intensifies during extreme market conditions compared to normal periods, indicating greater risk contagion in the tails of the distribution—effects that remain obscured under average market states. AI, cleantech, and Space are net shock receivers, while both Robotics and Auto-Vehc are net shock transmitters at both short- and long-terms. For the reaming stocks, they shift from net receives to net contributors and vice versa according to the time investment horizon. The short-term spillover is stronger during bull market scenario than bear market whereas the long-term spillover is higher during bear than bull market. AI and Smart-Fact stocks are net shock receivers irrespective of the market regime and time investment horizon. Space stock is net shock transmitter in the system for all market conditions and time investment horizons.

This paper makes several contributions to the existing literature. To the best of our knowledge, this is the first attempt to measure the connectedness among major technology stock markets. Second, it identifies the temporal spillovers during different market regimes. Specifically, this study explored the connectedness size and direction across technology sector stocks during bear and bull market modes. Investor's anticipation and risk appetite depend on the market situation. Investors strive to limit the portfolio risk during bear market conditions and take risk to increase the expected return during bullish market conditions. More importantly, speculators are short-term investors and are concerned by the spillover across market at short term while institutional investors are long-term investors and focus on the long-term spillovers. Therefore, understanding the dynamic spillover across different time investment horizons provides useful insights to market participants in terms of portfolio management and informative decision. Third, the study introduces a regime-aware, horizon-specific connectedness model that can be operationalized by institutional investors and risk managers. This enables more responsive portfolio rebalancing and hedging strategies, especially under volatile or uncertain market regimes. Fourth, the integration of time-frequency connectedness with real-time regime shifts contributes to the growing field of financial analytics underpinned by big data and AI. The analytical tools employed in this study (e.g., rolling window VAR, frequency decomposition) can be embedded into data-driven investment platforms and AI-assisted trading algorithms for continuous monitoring of systemic risk and asset dependencies. Fifth, this study has critical policy relevance: it helps identify which technology subsectors act as consistent transmitters of risk during turbulent periods. This insight supports regulators and central banks in building early warning systems and sector-specific macroprudential policies, particularly in economies with high exposure to digital and tech-driven industries. Finally, our results advance both theoretical understanding and practical application by integrating the connectedness framework within the context of new economy technology sectors—an emerging and increasingly influential component of global markets. This focus addresses a timely issue, as digital transformation reshapes investment patterns, sectoral interdependence, and risk transmission channels.

The remainder of this paper is structured as follows: Sections 2 and 3 explain the methodology and data. Section 4 presents the findings, while Section 5 concludes.

2. Methodology and data:

1.1. Quantile frequency connectedness

We employ the quantile connectedness approach of Ando et al. (2022), which allows us to uncover the connectedness in various quantiles (τ) such as bearish $(\tau=0.05)$, normal $(\tau=0.5)$, and bullish $(\tau=0.95)$ market conditions. The quantile vector autoregression (QVAR) process is constructed by its moving average (MA) representation as follows:

$$y_t = \mu(\tau) + \sum_j^p \Phi_j(\tau)\, y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) u_{t-i} \qquad (1)$$

Following Koop et al. (1996) and Pesaran and Shin (1998), the generalized forecast error variance decomposition (GFEVD) with a forecast horizon is defined as

$$\Theta_{ij}(H) = \frac{(\Sigma(\tau))_{jj}^{-1} \Sigma_{h=0}^{H}\left(\left(\Psi_h(\tau)\Sigma(\tau)\right)_{ij}\right)^2}{\Sigma_{h=0}^{H}\left(\Psi_h(\tau)\Sigma(\tau)\Psi_h'(\tau)\right)_{ii}}, \qquad (2)$$

$$\widetilde{\Theta}_{ij}(H) = \frac{\Theta_{ij}(H)}{\sum_{k=1}^{N}\Theta_{ij}(H)}, \qquad (3)$$

where $\sum_{i=1}^{N}\widetilde{\Theta}_{ij} = 1$ and $\sum_{i,j=1}^{N}\widetilde{\Theta}_{ij}(H) = N$.

The "TO" directional connectedness index measures how much of a shock in the market is transmitted to all other markets j:

$$TO_i(H) = \frac{\sum_{i=1, i\neq j}^{N}\widetilde{\Theta}_{ji}(\tau)}{\sum_{k=1}^{N}\widetilde{\Theta}_{ji}(\tau)} \times 100 \qquad (4)$$

The "FROM" directional connectedness index captures how much market is receiving from shocks in all other markets j:

$$FROM_i(H) = \frac{\sum_{i=1, i\neq j}^{N}\widetilde{\Theta}_{ij}(\tau)}{\sum_{k=1}^{N}\widetilde{\Theta}_{ij}(\tau)} \times 100 \qquad (5)$$

The "NET" directional connectedness index represents the different between TO and FROM connectedness index as follows:

$$NET_i(H) = TO_i(H) - FROM_i(H) \qquad (6)$$

The $NET_i(H) > 0$ $(NET_i(H) < 0)$ indicates a net transmitter (net receiver) of shocks.

The total connectedness index measures the interconnectedness can be calculated as:

$$TCI(H) = \frac{\sum_{i-1}^{N}\sum_{j=1,i\neq j}^{N}\tilde{\Theta}_{ij}(\tau)}{\sum_{i-1}^{N}\sum_{j=1}^{N}\tilde{\Theta}_{ij}(\tau)} \times 100 \quad (7)$$

Following the quantile frequency connectedness index of Chatziantoniou et al. (2022), we measure the decomposition of the connectedness index in the time domain into different frequency bands through the spectral representation of variance decomposition. First, we consider the frequency response function $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$ where $i = \sqrt{-1}$. The spectral density of X_T at frequency ω which can be defined as a Fourier transformation of the QVMA (∞) representation:

$$S_X(\omega) = \sum_{h=0}^{\infty} E(X_t X'_{t-h})e^{-i\omega h} = \Psi(e^{-i\omega h})\Sigma\Psi'(e^{i\omega h}), \quad (8)$$

The frequency GFEVD at frequency can be defined as:

$$\Theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Psi(\tau)(e^{-i\omega h})\Sigma(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}\left(\Psi(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h})\right)_{ii}}, \quad (9)$$

Eq (9) can be normalized as:

$$\breve{\Theta}_{ij}(\omega) = \frac{\Theta_{ij}(\omega)}{\sum_{k=1}^{N}\Theta_{ij}(\omega)}, \quad (10)$$

where Θ̆_ij (ω) measures the portion of the spectrum of the market i at a given frequency ω that can be attributed to a shock in the market j. The GFEVD on a frequency band g=(c,d):c,d∈(-π,π), c<d, , can be expressed as:

$$\breve{\Theta}_{ij}(g) = \int_c^d \breve{\Theta}_{ij}(\omega) g\omega. \quad (11)$$

The total connectedness index TCI(g) within the frequency band , is expressed as:

$$TCI(g) = \frac{\sum_{i=1,i\neq j}^{N}\breve{\Theta}_{ij}(g)}{\sum_{ij}\breve{\Theta}_{ij}(g)} = 1 - \frac{\sum_{i=1}^{N}\breve{\theta}_{ii}(g)}{\sum_{ij}\breve{\theta}_{ij}(g)} \quad (12)$$

The directional connectedness (FROM) from market to all other markets is computed as:

$$FROM_i(g) = \sum_{j=1,j\neq i}\breve{\Theta}_{ij}(g), \quad (13)$$

The directional connectedness (TO) from all other markets to market is defined as:

$$TO_i(g) = \sum_{j=1,i\neq j} \breve{\Theta}_{ij}(g) \,, \tag{14}$$

Finally, the net directional connectedness can be computed as:

$$NET_i(g) = TO_i(g) - FROM_i(g), \tag{15}$$

In our case, we have two frequency bands illustrating short-term 15- days, g_1=(π/5,π) in the high-frequency band and long-term 5-infinite days, g_2=(0,π/5) in the low-frequency band, respectively.

1.2. Data and descriptive analysis:

We employ the daily close prices of nine technology sector indices, namely S&P Kensho Artificial Intelligence (AI), S&P Kensho Cleantech (Cleantech), S&P Kensho Space (Space), S&P Kensho Smart Factories (Smart-Fact), S&P Kensho Enterprise Collaboration (Ent-Collabor), S&P Kensho Robotics (Robotics), S&P Kensho Autonomous Vehicles (Auto-Vehc), S&P Kensho Digital Communities (Dig-Comm), S&P Kensho Alternative Finance (Alt-Fin). The selection of these nine S&P Kensho indices is motivated by their comprehensive representation of disruptive innovation and the evolving landscape of the new economy. Each index captures a distinct technological frontier—ranging from AI and robotics to clean technologies, digital finance, and space exploration—allowing us to examine interconnectedness across diverse innovation-driven sectors. These indices are constructed based on objective criteria and include a wide range of firms actively involved in their respective domains, offering a balanced and diversified proxy for each theme. This approach enables a more structured analysis of cross-sectoral spillovers compared to using individual stocks, which are subject to idiosyncratic noise. By focusing on these indices, we ensure analytical consistency and relevance in understanding the dynamic interplay among key future-oriented sectors. The dataset is sourced from Bloomberg. Our dataset spans from March 13, 2018, to January 10, 2025. The sample period convers major economic and geopolitical events including the Ukraine-Russia tension, COVID19 pandemic, U.S.–China Trade War and 2025 Tariff Truce, Failures of U.S. regional banks like Silicon Valley Bank and Signature Bank, along with Credit Suisse's crisis, Middle East conflicts, AI Safety Summit in 2023.

Returns were calculated as continuously compounded daily returns: $r\_t=\ln(P_T/P_{T-1})\times 100$.. Fig. 1 illustrates the price series and shows that all stock prices exhibit large swings. All stocks show a decline in early 2020 followed by an upside trend in mid-2020 and a second downside trend during 2022. The large oscillations in these technology sectors are explained by their vulnerability to external shocks. Fig. 2 plots the price return series and indicates a significant fat tails and leptokurtic effects.

The descriptive statistics of stock price returns are reported in Panel A of Table 1. As we can see, all stocks have positive mean return except for Alt-Fin stock. Ent-Collabor stock has the highest mean return followed by AI stock and Cleantech stock. The last stock is the highest risky market followed by Auto-Vehc and Alt-Fin stocks whereas Space stock is the least risky one. All return series are asymmetric as defined by skewness test and leptokurtic as determined by kurtosis test. The results of Jarque Bera test rejects the null hypothesis of normal distribution. The ERS test shows that the return series are stationary. Panel B of Table 1 shows the correlation matrix among all stock return series. We observe that AI stock is negatively correlated with all other technology stocks, underlying hedging opportunities. Smart-Fact stock is weakly correlated with the remaining technology stocks where the correlation is less than 0.3, indicating diversification gains. The correlations among other technology stocks are high, suggesting an increasing integration among these stocks.

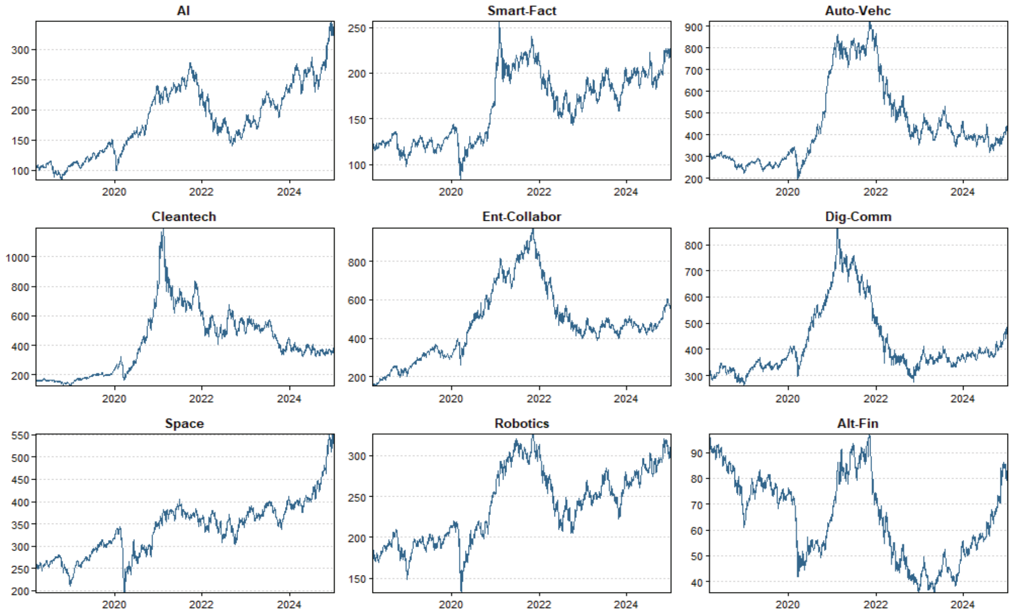


Fig. 1. Dynamic of stock prices

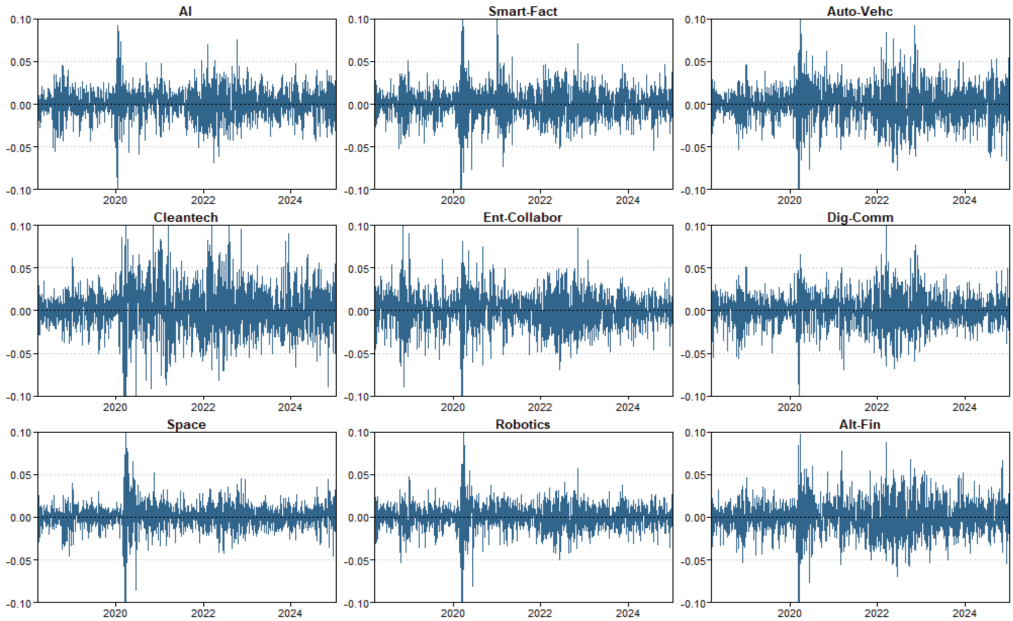


Fig. 2. Dynamic of stock returns

Table 1: Descriptive statistics

Panel A : Summary statistics									
	AI	Cleantech	Space	Smart.Fact	Ent.Collabor	Robotics	Auto.Vehc	Dig.Comm	Alt.Fin
Mean	0.0663	0.0479	0.0414	0.0311	0.0698	0.0287	0.0157	0.0192	-0.0129
.Std. Dev	1.7973	2.7544	1.5286	1.8618	2.094	1.5347	2.1956	1.9431	2.0513
Skewness	***-0.413	**-0.125	***-0.866	**-0.150	***-0.198	***-0.582	***-0.360	-0.005	***-0.259
Ex.Kurtosis	***3.705	***2.827	***12.188	***5.089	***2.590	***7.393	***2.983	***3.170	***3.262
JB	***1032.1	***576.7		***1861.2	***491.7	***4011.4	***674.2	***719.7	***781.5
ERS	***-6.067	***-14.987		***-10.301	***-7.547	***-10.147	***-13.116	***-8.707	***-8.701
(Q(10	***32.7	**13.4	***63.8	***31.7	7.1	***59.9	***18.7	**12.2	**13.174
(Q2(10	***789.4	***442.7	***1415.9	***673.5	***399.4	***1011.4	***522.5	***323.8	

Follow: Table 1: Descriptive statistics

Panel B: Spearman correlation									
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin
AI	***1.000								
Cleantech	-0.034	***1.000							
Space	-0.013	***0.614	***1.000						
Smart-Fact	-0.028	***0.236	***0.248	***1.000					
Ent-Colla-bor	-0.031	***0.571	***0.548	***0.229	***1.000				
Robotics	-0.020	***0.669	***0.796	***0.273	***0.639	***1.000			
Auto-Vehc	-0.019	***0.720	***0.670	***0.292	***0.658	***0.764	***1.000		
Dig-Comm	-0.002	***0.621	***0.532	***0.223	***0.690	***0.657	***0.729	***1.000	
Alt-Fin	-0.012	***0.648	***0.707	***0.260	***0.629	***0.754	***0.758	***0.676	***1.000

Notes: This table reports return series statistics (Panel A) and Spearman correlations (Panel B): skewness (D'Agostino. 1970). kurtosis (Anscombe & Glynn. 1983). normality (Jarque-Bera. 1980). stationarity (ERS. 1996). and autocorrelation (Q(10) and Q- (10). Fisher & Gallagher. 2012). ** and *** indicate significance at the 5% and 1% levels. respectively.

3.Results and discussions:

3.1. Connectedness analysis during tranquil market:

Table 2 presents the averaged frequency connectedness at intermediate quantile (normal market scenario). The total connectedness index among stocks is high (63.7%). Moreover, the short-term connectedness is stronger than the long-term connectedness during normal market mode. This indicates that the spillover effects do not persist for a long time and that the market absorbs information quickly. These findings support the Heterogeneous Market Hypothesis (HMH), which posits that market participants operate with diverse expectations, investment horizons, and reaction times, leading to asymmetric responses to information and varying degrees of connectedness across different time scales. These findings are consistent with prior empirical evidence (Alomari et al., 2024; Mensi et al., 2023; Yousaf et al., 2024), which highlights the predominance of short-term connectedness over long-term spillovers. AI, Cleantech, and Space stocks are net shock receivers across different time horizons. In contrast, Robotics stock is a net shock transmitter in the system. This reveals that this stock amplify risk in portfolio during times of market stress. For the other markets, they role change from net shock receiver to net shock transmitter and vice versa, depending of the time investment horizons. This result indicates the dominance of these stocks in the market in terms of market capitalization and trading volume. It also due to the increased sensitivity of these stocks to global and macroeconomic shocks. These results carry important implications for institutional investors, portfolio managers, and financial practitioners, as they emphasize the need for horizon-sensitive risk management strategies and sector-specific positioning. Moreover, by identifying systemic transmitters such as Robotics, the analysis provides regulators and policymakers with insights into potential sources of market instability, which can inform the design of sector-focused financial oversight and macroprudential policies.

Table 2: Averaged frequency connectedness at conditional mean (Q = 0.5)

Total										
	AI	**Cleantech**		**Smart-Fact**	**Ent-Collabor**	**Robotics**	**Auto-Vehc**	**Dig-Comm**	**Alt-Fin**	**FROM**
AI	80.94	2.43	2.19	2.55	2.81	2.49	2.40	2.12	2.08	19.06
Cleantech	0.80	27.93	10.66	4.67	8.80	12.23	13.50	10.06	11.35	72.07
Space	0.87	10.39	26.84	5.10	8.65	16.14	11.55	8.10	12.36	73.16
Smart-Fact	1.76	4.91	5.34	59.86	5.65	6.07	6.37	4.60	5.44	40.14
Ent-Collabor	0.96	9.05	8.91	5.36	29.49	10.85	11.39	13.12	10.86	70.51
Robotics	0.64	10.57	14.25	5.51	9.27	24.13	13.25	9.98	12.40	75.87
Auto-Vehc	0.69	11.70	10.49	5.61	9.59	13.34	23.92	11.98	12.70	76.08
Dig-Comm	0.90	9.80	8.18	4.50	12.34	11.17	13.64	27.59	11.87	72.41
Alt-Fin	0.75	10.31	11.66	4.99	9.61	13.11	13.21	10.95	25.41	74.59
TO	7.38	69.18	71.68	38.31	66.69	85.38	85.30	70.90	79.06	573.90
Inc.Own	88.32	97.11	98.53	98.17	96.18	109.51	109.22	98.49	104.47	**TCI**
Net	-11.68	-2.89	-1.47	-1.83	-3.82	9.51	9.22	-1.51	4.47	**63.77**
days 1-5										
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin	FROM
AI	73.72	2.19	1.96	2.29	2.54	2.15	2.13	1.91	1.83	16.99
Cleantech	0.70	25.36	9.56	4.13	7.98	10.90	12.32	9.08	10.26	64.92
Space	0.80	9.37	24.36	4.61	7.79	14.49	10.51	7.27	11.17	66.01
Smart-Fact	1.56	4.42	4.72	54.24	5.08	5.44	5.78	4.20	4.92	36.13
Ent-Collabor	0.87	8.20	8.12	4.72	26.58	9.84	10.48	11.96	9.94	64.12
Robotics	0.56	9.44	12.78	4.86	8.28	21.53	11.93	8.87	11.15	67.86

Follow : Table 2: Averaged frequency connectedness at conditional mean (Q = 0.5)

Total										
	AI	**Cleantech**		**Smart-Fact**	**Ent-Collabor**	**Robotics**	**Auto-Vehc**	**Dig-Comm**	**Alt-Fin**	**FROM**
Auto-Vehc	0.62	10.61	9.45	4.98	8.67	12.03	21.73	10.92	11.50	68.78
Dig-Comm	0.79	8.91	7.49	4.05	11.27	10.14	12.53	25.11	10.92	66.10
Alt-Fin	0.67	9.23	10.55	4.44	8.64	11.69	11.90	9.79	23.03	66.91
TO	6.57	62.39	64.62	34.08	60.23	76.68	77.57	64.00	71.70	517.83
Inc.Own	80.29	87.75	88.97	88.32	86.81	98.21	99.30	89.11	94.73	**TCI**
Net	-10.42	-2.53	-1.40	-2.04	-3.89	8.82	8.79	-2.11	4.78	**57.54**
5-Inf										
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin	FROM
AI	7.22	0.24	0.23	0.26	0.27	0.34	0.27	0.21	0.25	2.07
Cleantech	0.10	2.57	1.10	0.55	0.82	1.33	1.18	0.97	1.09	7.14
Space	0.07	1.02	2.49	0.49	0.86	1.64	1.04	0.83	1.19	7.14
Smart-Fact	0.20	0.49	0.63	5.62	0.56	0.63	0.59	0.40	0.52	4.02
Ent-Collabor	0.10	0.85	0.80	0.64	2.91	1.02	0.91	1.16	0.92	6.39
Robotics	0.09	1.13	1.47	0.65	0.99	2.59	1.32	1.11	1.25	8.01
Auto-Vehc	0.07	1.09	1.04	0.63	0.91	1.31	2.19	1.06	1.19	7.30
Dig-Comm	0.11	0.89	0.70	0.45	1.07	1.03	1.12	2.48	0.95	6.31
Alt-Fin	0.08	1.08	1.11	0.56	0.97	1.41	1.31	1.16	2.38	7.68
TO	0.81	6.79	7.06	4.23	6.46	8.71	7.73	6.90	7.37	56.06
Inc.Own	8.03	9.36	9.55	9.85	9.38	11.30	9.92	9.38	9.74	**TCI**
Net	-1.26	-0.35	-0.08	0.21	0.07	0.69	0.43	0.60	-0.31	**6.23**

Notes: This table estimates connectedness using the quantile time-frequency approach (Chatziantoniou et al.. 2022) with a 100-day rolling-window QVAR model (1 lag length. 10-step forecast). The "FROM" column shows the connectedness received by market i. the "TO" row shows the connectedness it transfers. and the "NET" row displays the net connectedness.

The static spillover analysis hide important information on how the spillover index is influenced by major events. For this purpose, we use the rolling window approach to see the temporal spillover. Fig. 3 shows that the spillover is time-varying and crisis sensitive. The graph highlights that the short-term spillover dominates the long-term spillover for the whole sample period. More specifically, the short-term spillover varies from 45% to more than 70% in early 2020. The long-term spillover varies between 5% to 25% and reaches its maximum in 2019. These patterns underscore the importance for policy authorities to monitor short-horizon financial linkages during periods of systemic stress, as they can transmit volatility rapidly across sectors. Fig. 4 displays the dynamic net connectedness at medium quantile. The graphical evidence indicates that Robotics stock is a net shock transmitter at both short and long terms for the whole period. The results are nearly similar for and Auto-Vehc stock. AI and Space stocks are net shock receivers for the whole period. For the remaining stocks they oscillate between net shock receivers and transmitters, underlying their vulnerability to global shocks and time horizons. These results are particularly relevant for investors and corporate risk managers who must adapt their hedging and allocation strategies dynamically based on evolving sectoral interdependencies. At the same time, the identification of consistently transmitting sectors provides regulators with early-warning signals of contagion pathways, warranting closer supervision of those industries during turbulent periods.

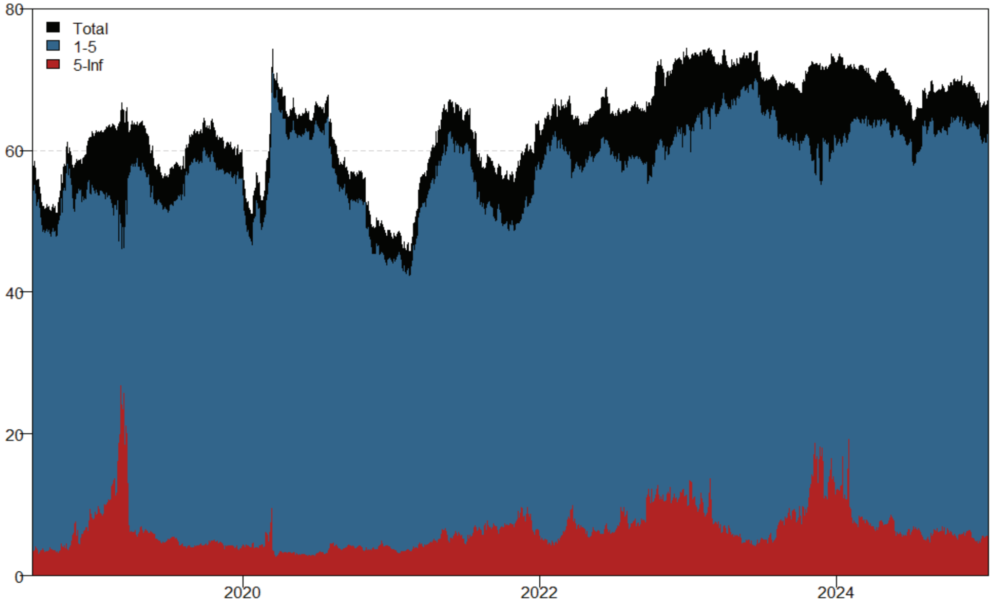


Fig. 3. Dynamic total frequency connectedness at medium quantile (q=0.5)

Notes: This figure depicts the time-varying Total Connectedness Index at the median quantile across various frequency bands. The indices are calculated using GFEVD with a 100-day rolling window and a 10-day forecast horizon. The black shaded area represents the overall connectedness at the median quantile. the blue-shaded area indicates short-term connectedness (15- days). and the red-shaded area shows long-term connectedness (5 days-Inf).

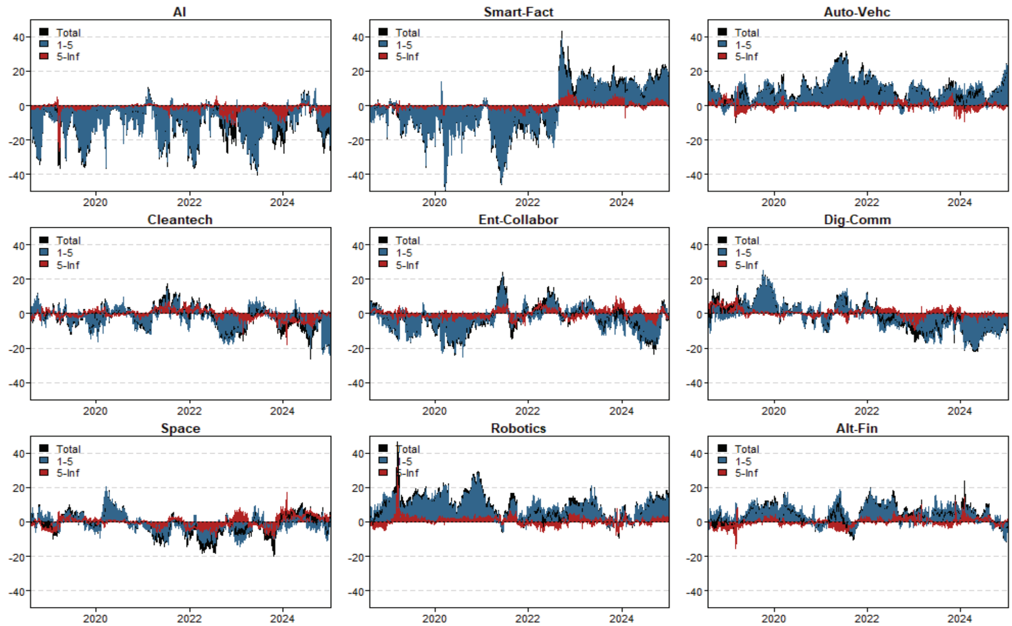


Fig. 4. Dynamic net frequency connectedness at medium quantile (q=0.5)

Notes: This chart shows the net time-frequency connectedness at the middle quantile. calculated by deducting the directional 'FROM' connectedness from the directional 'TO' connectedness at various frequency bands.

3.2. Quantile frequency connectedness :

Investors behaviors and anticipations depends on market regimes. Moreover, the market dynamics is sensitive to crisis periods. Investors seek to maximize their profit during bullish market conditions and limit risk during bearish market scenario. Table 3 presents the spillover effects across technology stock index returns during beat and bull markets scenarios and at both short and long terms.

Under bearish market mode, we show that the TCI is high (86.05%) for the whole sample period. The TCI is higher at short term (1 to 5 trading days) than long term. In addition, AI, and Smart-Fact stocks are net shock receivers in the system while, Cleantech and Space stocks are net shock contributors at different time horizons. In contrast, Ent-collabor, Robotics, and Dig-Comm stocks are net shock contributor in the short term and shift to net shock receiver in the long term, underlying the vulnerability of these stocks to global shocks in the long term. Auto-Vehc and Alt-Fin stocks are net shock receivers in the short term and net shock contributor in the long term. This shifting pattern across time horizons reveals the existence of sectoral risk rotation under bearish market conditions, which should guide policymakers in identifying which sectors act as shock absorbers versus amplifiers during downturns—helping prioritize liquidity support or sector-specific policy responses. Under the bull market, AI and Smart-Fact stocks remain shock receiver in the system irrespective of the time investment horizon. Similarly, Space stock is a net transmitter of shock at short and long term. This result is similar to the bearish market mode. However, Robtoics and Dig-Comm stocks become net shock contributors across different time horizons. Smart-Fact and Ent-Collabor stocks are net receivers of shocks while the remaining stocks oscillate between net shock receiver/ transmitter in the system, depending on the time investment horizon. This asymmetry between bullish and bearish regimes has direct implications for corporate strategy and strategic asset allocation: sectors that reverse roles between regimes require adaptive capital budgeting and hedging policies, particularly for firms operating in innovation-driven industries.

Table 3: Averaged frequency connectedness at lower (Q = 0.05) and upper (Q = 0.95) quantiles

Panel A: bear market scenario Q = 0.05										
Total										
	AI	**Cleantech**	**Space**	**Smart-Fact**	**Ent-Collabor**	**Robotics**	**Auto-Vehc**	**Dig-Comm**	**Alt-Fin**	
TO	68.95	89.61	92.40	79.98	91.28	88.88	88.77	87.27	87.33	TCI = 86.05
FROM	84.28	85.78	86.17	85.21	85.70	86.99	87.06	86.43	86.85	
Net	-15.34	3.84	6.23	-5.23	5.58	1.89	1.70	0.84	0.48	
days 1-5										
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin	
TO	56.53	74.08	77.84	65.25	74.68	74.39	73.91	72.07	73.15	TCI = 71.32
FROM	68.64	71.12	71.90	68.79	68.79	72.14	75.37	70.91	74.25	
Net	-12.11	2.96	5.95	-3.53	5.89	2.25	-1.46	1.15	-1.11	

5-Inf										
	AI	**Cleantech**	**Space**	**Smart-Fact**	**Ent-Collabor**	**Robotics**	**Auto-Vehc**	**Dig-Comm**	**Alt-Fin**	
TO	12.42	15.53	14.55	14.72	16.60	14.49	14.86	15.21	14.18	TCI = 14.73
FROM	15.64	14.66	14.27	16.42	16.91	14.86	11.69	15.51	12.60	
Net	-3.22	0.87	0.28	-1.70	-0.31	-0.37	3.16	-0.31	1.59	
Panel B: Bull market scenario Q=0.95										
Total										
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin	

Follow : Table 3: Averaged frequency connectedness at lower (Q = 0.05) and upper (Q = 0.95) quantiles

5-Inf										
	AI	**Cleantech**	**Space**	**Smart-Fact**	**Ent-Collabor**	**Robotics**	**Auto-Vehc**	**Dig-Comm**	**Alt-Fin**	
TO	70.86	87.53	86.95	77.81	84.87	91.20	88.89	89.13	88.79	TCI = 85.11
FROM	81.77	85.82	85.77	83.54	85.83	85.59	86.33	85.39	85.98	
Net	-10.91	1.71	1.18	-5.73	-0.96	5.61	2.56	3.73	2.81	
days 1-5										
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin	
TO	61.54	77.30	76.73	68.93	74.99	80.53	78.72	77.81	78.27	TCI = 74.98
FROM	72.37	74.44	76.57	73.22	75.63	76.80	74.93	75.64	75.22	
Net	-10.83	2.86	0.16	-4.28	-0.65	3.72	3.80	2.17	3.05	
5-Inf										
	AI	Cleantech	Space	Smart-Fact	Ent-Collabor	Robotics	Auto-Vehc	Dig-Comm	Alt-Fin	
TO	9.32	10.23	10.22	8.88	9.89	10.67	10.17	11.32	10.52	TCI = 10.13
FROM	9.40	11.38	9.20	10.32	10.20	8.79	11.40	9.76	10.76	
Net	-0.08	-1.15	1.02	-1.44	-0.31	1.89	-1.23	1.56	-0.24	

Note: See table 2

Fig. 5 illustrate the dynamic connectedness at the extreme tail level (right and left tails), where warmer shades indicate a higher level of connectedness.. In the medium quantile, the total connectedness remains ranges between 60% to 70% over the whole sample period, except in crisis periods such COVID-19 crisis and the Russia-Ukraine war. This result reveals that the spillover is more pronounced under normal market conditions where a global shock occurs. The spillover degree exceeds 90% at left and right tails. Such elevated tail connectedness points to a breakdown in diversification, reinforcing the challenge for investors and institutions to contain systemic risk when uncertainty is at its highest. These findings lend support to contagion theory (Forbes and Rigobon, 2002), which posits that financial shocks originating in one market or asset class can propagate rapidly to others, particularly during periods of heightened economic uncertainty or market distress, thereby exacerbating systemic risk and amplifying market interconnectedness. Such dynamics highlight the critical role of systemic risk monitoring and the need for regulatory frameworks that address the transmission channels of financial contagion to maintain market stability. The results of Fig. 6 confirm the findings in Table 3. Specifically, we observe that the short-term connectedness dominates the long-term spillover along the sample period and under extreme downside and upside market modes. The dominance of short-horizon spillovers underscores the importance of incorporating responsive mechanisms within risk management frameworks, as shocks tend to propagate rapidly, limiting the effectiveness of delayed strategic interventions.

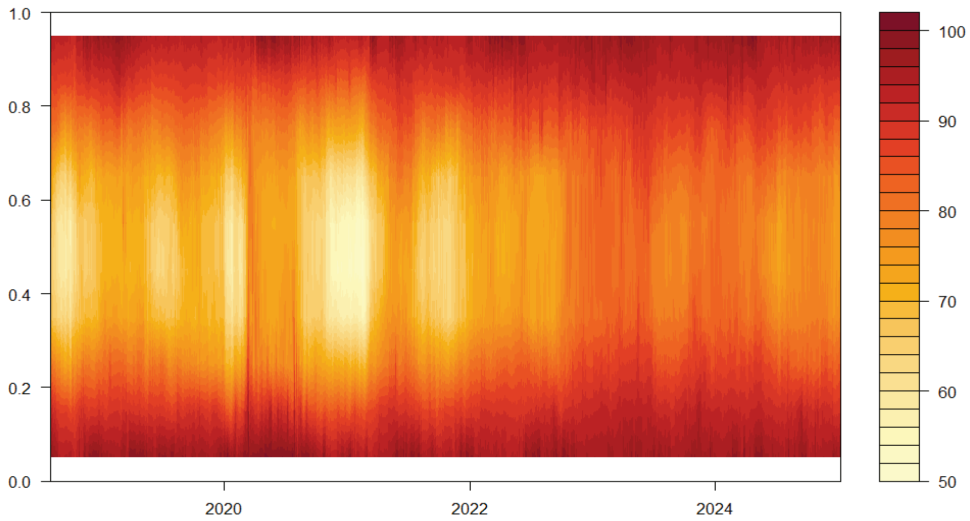
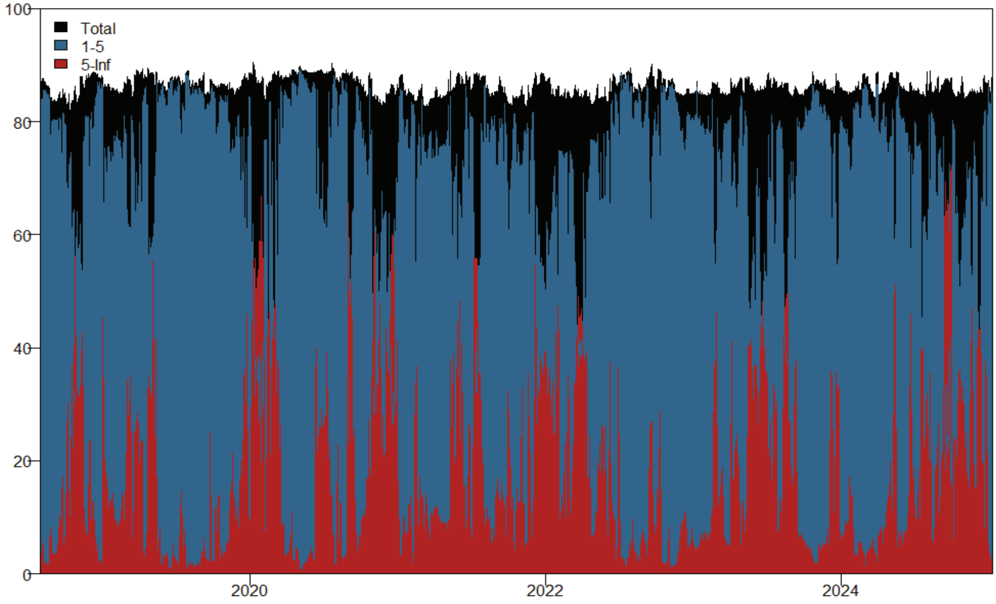


Fig. 5. Heatmap of dynamic total quantile connectedness



Q = 0.05

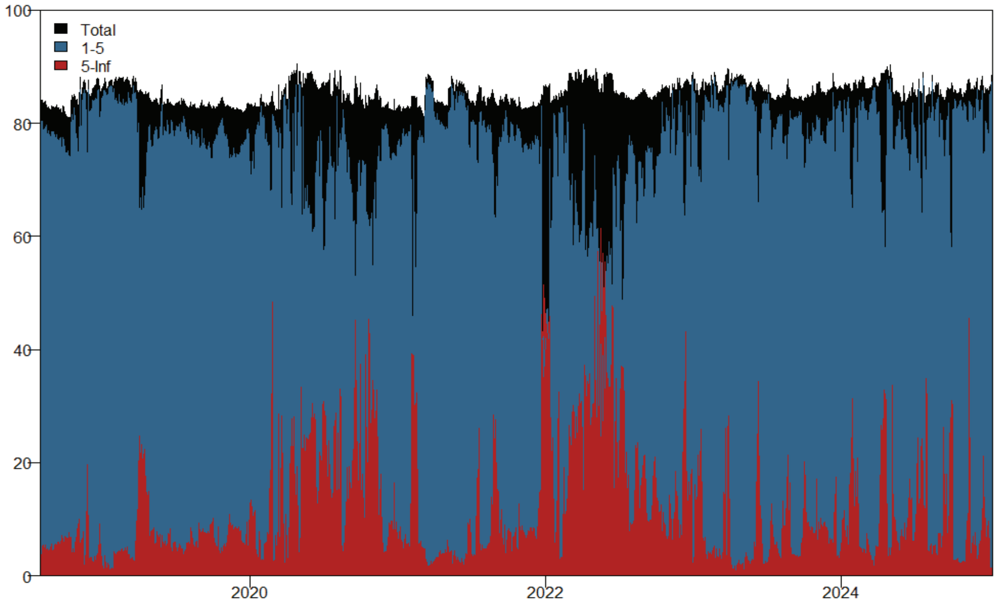


Fig. 6 Dynamic frequency connectedness at lower (Q=0.05) and upper (Q=0.95) quantiles

4. Conclusion:

This study examines the connectedness size and direction across technology stock markets namely S&P Kensho Artificial Intelligence (AI), S&P Kensho Cleantech (Cleantech), S&P Kensho Space (Space), S&P Kensho Smart Factories (Smart-Fact), S&P Kensho Enterprise Collaboration (Ent-Collabor), S&P Kensho Robotics (Robotics), S&P Kensho Autonomous Vehicles (Auto-Vehc), S&P Kensho Digital Communities (Dig-Comm), S&P Kensho Alternative Finance (Alt-Fin). We employ the quantile frequency connectedness model developed by Chatziantoniou et al. (2022) to assess risk spillovers among AI-related sectors under different market scenarios—specifically bear and bull markets—across both short- and long-term horizons. The data spans from March 13, 2018, to January 10, 2025, a period that captures several major economic and geopolitical events.

Our results show strong connectedness among the markets under investigation. Moreover, we find that the large portion of total spillover comes from the short term as the short-term spillover dominates the long-term spillover during the normal market scenarios. This result persists during bear and bull market conditions. In addition, the long-term spillover is higher during bear than bull market. In contrast, the short-term spillover is high during bull market. During normal market period, AI, Cleantech, and Space stocks are net shock receivers in the system at both short and long terms. In contrast, Robotics and Auto-Vehc stocks are net shock contributors for different time horizons. Smart-Fact, Ent-Collabor, and Dig-Comm stocks are net shock receivers in the short term and shift to net shock contributors in the long term. However, Alt-Fin stock is net shock transmitter in the short term and net receivers of shocks in the long term. During extreme market movements, we observe that the spillover the short-term spillover is stronger than the long-term spillover during bear and bull market periods. Interestingly, the short-term spillover during bull market condition than in the bear market condition, while the long-term spillover is higher during bear than bull market mode. AI and Smart-Fact (Space) stock is net shock receivers (transmitters) irrespective of market conditions and time investment horizons. However, for the remaining technology stocks, their role changes from net receiver to net contributor of shocks according to market conditions and investment horizons.

The findings of this study have several important implications for investors, portfolio managers, and policymakers. Our results reveal that spillovers among AI-driven technology stocks are both time- and frequency-dependent, with stronger connectedness in the short term across all market regimes. Notably, during bull markets, the short-term connectedness intensifies, signaling rapid transmission of shocks over shorter horizons, particularly for stocks such as Space and Alt-Fin, which consistently act as shock transmitters. This presents elevated short-term contagion risk for investors during optimistic market conditions. Conversely, during bear markets, long-term connectedness becomes more pronounced, suggesting persistent interdependence and slower-moving spillovers, likely driven by structural or fundamental linkages between sectors. These patterns underscore the importance of adopting dynamic investment strategies. Investors should avoid treating technology subsectors as homogeneous; instead, they should distinguish between persistent net receivers (e.g., AI and Smart-Fact) and net transmitters (e.g., Space) when designing hedging or diversification strategies. Portfolio managers may enhance performance by incorporating quantile-frequency measures of connectedness into asset allocation frameworks, thereby adapting exposure not only to changing market sentiments (bear, bull, or normal) but also to different time horizons. From a regulatory standpoint, the identification of consistently shock-transmitting sectors allows financial supervisors to prioritize macroprudential oversight and apply pre-emptive stress-testing tools to mitigate systemic risk. For example, the persistent role of Space stocks as a shock transmitter calls for sector-specific surveillance during both expansionary and contractionary periods. Moreover, the frequency asymmetry in spillover dynamics calls for coordinated regulatory interventions targeting both short-term volatility management and long-term stability enhancement.

These findings are in line with financial contagion theory, which suggests that interdependence among markets intensifies during periods of stress or extreme optimism, leading to a higher likelihood of systemic transmission of shocks. Moreover, the asymmetric spillover effects across frequencies and quantiles support the Heterogeneous Market Hypothesis (HMH), which posits that market participants operate on different time horizons and react asymmetrically to information. In particular, the elevated short-term spillovers in bullish conditions reflect herding and sentiment-driven behavior, while long-term spillovers during bearish periods may be attributed to fundamental economic ties. Additionally, the abrupt shifts in directional connectedness and transmission roles among the sectors, particularly during crises, align with the Black Swan theory, as they point to rare but high-impact events that significantly reshape the connectedness structure in unexpected ways.

However, this study is not without its limitations. First, the analysis is restricted to a group of AI-related technology sectors, excluding their potential interconnections with broader financial markets, particularly green financial markets. This is a notable limitation, given the growing intersection between technological innovation and sustainability concerns. Ignoring this dimension may underestimate the systemic risk implications of sectoral interconnectedness, especially as investors increasingly view technological and environmental risks as interlinked. Second, the study does not examine the determinants of the observed spillovers, such as macroeconomic uncertainty, volatility measures, or investor sentiment. Understanding the driving forces behind connectedness dynamics would provide deeper insight into whether these spillovers are driven by fundamentals, behavioral factors, or exogenous shocks. Integrating such variables could enhance the explanatory and predictive power of the model.

Future research could address these limitations by incorporating inter-sectoral linkages between technology and green finance, ESG-aligned assets, or climate-risk-sensitive portfolios. Extending the model to include explanatory factors such as VIX, policy uncertainty indices, and sentiment proxies would help disentangle the channels through which shocks are transmitted. Additionally, adopting regime-switching, time-varying, or nonlinear causality models could capture more complex and evolving structures of connectedness. Finally, applying this framework to a cross-country setting would offer comparative insights into how technological spillovers operate in different regulatory and economic environments.

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