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DYNAMIC VOLATILITY SPILLOVERS AMONG MAJOR US TECHNOLOGY COMPANIES: A TIME-VARYING CONNECTEDNESS ANALYSIS

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Abstract

The technology sector's rapid growth and increasing market concentration have fundamentally altered market dynamics and volatility patterns among leading firms. This study investigates the volatility spillovers among nine major US technology companies. Specifically, the study captures the interdependence and the level of influence corresponding to the stock return volatilities of these firms on one another. Apple, Amazon, Google, IBM, Intel, Meta, Microsoft, Nvidia, and Tesla were sourced from Investing.com. The daily data was collected between April 1, 2014, and May 31, 2024. We apply the Connectedness Approach framework to the time-varying parameter vector autoregression model. This methodology estimates several metrics: the total connectedness index, directional measures of volatility transmission, and pairwise relationship indicators. The analysis shows that Microsoft and Google emerge as dominant net transmitters, while IBM and Intel function as primary receivers. Tesla's receiver status despite large market capitalization confirms that ecosystem positioning rather than market size determines transmission hierarchy. The Total Connectedness Index shows significant variation during market crises, intensifying spillovers while preserving network structure. Amazon and Nvidia demonstrate variable transmission capacity. This study contributes to the literature by providing a comprehensive analysis of time-varying volatility transmission networks among leading technology firms, revealing systemic risk patterns and network effects crucial for investment and regulatory decision-making.

Keywords: connectedness analysis, network analysis, stock return volatility, technology

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1. Introduction

The last 10 years have seen the technology industry go through a period of unprecedented growth and market concentration, and as such, redefine the very nature of market forces and volatility between the key players of this industry. This sharp transformation indicates a paradigm adjustment in the modern financial markets. The technology companies have market capitalizations equivalent to the size of many sovereign economies and have areas of influence that go far beyond the traditional industry boundaries (Mueller et al., 2017). The emergence of platform business models and ecosystem dependencies, coupled with the network effects, has overlaid webs of interdependence that inherently interrogate conventional thinking in relation to sector specificity risk and market segmentation. The existing business models that competed in an unchanged competitive landscape have been disrupted on the one hand, along with frameworks redefined through digital transformation, platform economics, and technological innovation, resulting in the creation of new channels of volatility transmission (Sjödin et al., 2023; Xing et al., 2019). The technological interdependencies work through various channels of supply chain relations, platform ecosystem dependencies, regulatory exposures, and innovation cycles, thus providing systematic transmission channels and may be prone to magnifying volatility than a traditional financial theory would have expected.

While an extensive empirical body has examined volatility transmission across financial markets and economic sectors, research on technology-sector-specific spillovers remains disjointed and theoretically underdeveloped (Bas et al., 2024; Umar et al., 2024). Existing literature has the tendency to treat technology companies as homogeneous entities within broader sectoral studies, thus ignoring the distinct roles these companies fulfil in closely connected technological ecosystems. Despite the growing importance of major technology companies in global markets, as leading technology firms assume roles as market-infrastructure providers rather than conventional technology enterprises, a crucial gap has opened in our grasp of how these organizations engage within intricate ecosystem networks and to what extent such ties shape systemic risk. This gap carries heightened significance, for the leading technology firms collectively command more than $10 trillion in market capitalization (Tirole, 2023) and furnish critical infrastructure to a broad spectrum of other enterprises via their platform services, cloud-computing platforms, and orchestration of networked ecosystems.

Technology companies' business models, characterized by network effects, platform dependencies, and innovation cycles, create unique market dynamics that distinguish them from traditional sectors. Unlike conventional industries where firms compete primarily through product differentiation and operational efficiency, technology companies engage in ecosystem competition where success depends on network effects, platform adoption, and technological standard-setting (Gawer & Cusumano, 2014). This fundamental difference in competitive dynamics creates distinct volatility transmission mechanisms that traditional financial models may inadequately capture. The sector's unique characteristics—including high intangible asset valuations, winner-take-all market dynamics, and regulatory uncertainty—create information processing challenges that may lead to correlated reactions and systematic mispricing during periods of uncertainty (Intara & Suwansin, 2024). As technology companies continue to grow in market influence and systemic importance, understanding these transmission mechanisms is crucial for investors, regulators, and market participants. The potential for technology sector volatility to cascade through broader financial markets has become a critical concern for financial stability, particularly as passive investment strategies and sector-based funds have increased correlation among technology stocks beyond what fundamental relationships would suggest.

This paper investigates volatility spillovers among nine major US technology companies, selected based on their systemic importance and representative ecosystem roles. Our analysis employs an ecosystem-based framework that recognizes these firms as distinct participants in an interconnected technological ecosystem, where each firm occupies specific functional roles—from platform infrastructure providers to consumer interface controllers to hardware foundation suppliers. The study captures the interdependence and levels of influence of stock return volatilities among these firms, providing insights into the influential roles of significant technology companies in the modern market landscape. By applying time-varying connectedness analysis to this ecosystem-representative sample, we reveal the dynamic evolution of volatility transmission networks and the emergence of hub-and-spoke patterns that reflect underlying technological dependencies. Our approach addresses a critical limitation in existing research: the failure to account for heterogeneous roles that different technology companies play within the broader technological ecosystem and how these roles influence their positions in volatility transmission networks.

The contributions of this study are threefold. First, we develop an ecosystem-based theoretical framework that explains why certain technology companies consistently emerge as volatility transmitters while others function as receivers, providing theoretical grounding that existing spillover studies have largely ignored. Second, by employing the Connectedness Approach framework, we conduct a comprehensive analysis of volatility spillovers encompassing total connectedness, directional connectedness, and pairwise transmission across our ecosystem-representative sample. Third, our analysis demonstrates that traditional market capitalisation-based explanations for volatility leadership are insufficient; instead, ecosystem positioning and platform control emerge as primary determinants of transmission hierarchy, offering new insights for both academic research and practical risk management.

Our findings have direct implications for multiple stakeholders. For academic research, we contribute to the intersection of technology economics and financial market dynamics by demonstrating how technological ecosystem theory can inform volatility transmission analysis. For market participants, our identification of specific firms that function as volatility transmission hubs provides actionable intelligence for portfolio managers seeking to optimize hedging strategies and risk management practices. For regulators and policymakers, our results suggest that regulatory frameworks may need to evolve beyond traditional financial institution oversight to encompass technology platform providers whose ecosystem influence creates new forms of systemic risk. By revealing the systematic nature of technology sector interdependencies, this research contributes to understanding financial market stability in an era where technology companies serve as critical market infrastructure.

2. Literature Review

2.1 Technology Sector Characteristics and Market Dynamics

In the global financial markets, the technology industry has already formed a dominant force characterized by rapid innovation cycles, strong network effects, and significant market concentration among the dominant players. Such a transformation represents a fundamental shift in economic organization: technology firms have assumed the role of critical infrastructure providers and ecosystem orchestrators, with value creation processes radically different from those of industrial firms (Jacobides et al., 2018). Technology companies exhibit unique characteristics that distinguish them from the traditional industries: high growth volatility, substantial investments in research and development, platform-based business models, and strong ecosystem-dependency (Abed Alghani et al., 2024). These firms often experience amplified market reactions to innovation announcements, regulatory changes, and competitive developments, thus creating volatility patterns that warrant specialized analysis and challenge conventional financial theories by introducing non-linear feedback effects and threshold dynamics that are absent in more traditional industries.

Platform economics makes for an additional hallmark, distinguishing and transformative dimension of contemporary technology enterprises, creating unique interdependence configurations that evade the traditional industrial organizational framework. Many leading technology firms operate multi-sided platforms that create value by facilitating interactions between different user groups (Abed Alghani et al., 2024). This kind of platform-based model creates strong network externalities where the value of the platform grows with the number of participants and thus provides substantial competitive advantages, and at the same time creates a complex web of interdependencies whose propagation dynamics are unlike those in standard supply-demand relationships. Platform leaders, such as Microsoft (enterprise software), Google (advertising and cloud), and Amazon (e-commerce and cloud) serve as critical infrastructure on which numerous other businesses rely, with that interdependence escalating their impact on volatility trends in a given sector and systematically eroding established conceptions of industry boundaries, thus creating systematic dependencies that cross-cut conventional definitions of the sector (van der Vlist et al., 2024).

Market concentration within the technology sector has reached unprecedented levels, with a small number of companies having such significant amounts of market capitalization and control that they create systemically important financial institutions outside the traditional banking sector. Apple, Microsoft, Amazon, Google, and several other similar businesses collectively share a significant proportion of both dominant indices and total market capitalization (Gawer, 2024). This occurrence raises important questions about market efficiency and competitive organization, and, at the same time, creates potential single points of failure in the wider financial system. This concentration creates potential systemic risk, as negative happenings to these companies can create excessive imbalance across the market, suggesting that it may be crucial to expand the traditional approach to the role of too-big-to-fail companies to incorporate technology businesses whose ecosystem impact is substantially larger than their real market presence (Tirole, 2023).

2.2 Theoretical Foundations of Volatility Spillovers

Information-transmission theory provides the foundational framework for understanding volatility spillovers across financial markets through three main channels: fundamental linkages based on economic ties, behavioural linkages driven by herding and investor sentiment, and pure contagion effects spreading through markets without fundamental connections (Forbes & Rigobon, 2002). In technology companies, these channels are amplified by industry-specific dynamics that create complex interdependencies and informational asymmetries. Technology sector fundamental linkages operate through direct channels, including supply chain relationships, strategic partnerships, and competitive dynamics, alongside indirect channels through shared regulatory, technological, and macroeconomic risk exposures. Semiconductor companies like Intel and NVIDIA exemplify direct linkages by supplying critical components across the value chain, creating operational shock transmission pathways. Behavioural linkages gain prominence due to technology's high visibility in investor portfolios and unique investment characteristics, triggering distinct cognitive biases. The representativeness heuristic leads to style investing, where funds allocate based on sector classifications rather than fundamental characteristics (Barberis & Shleifer, 2003), amplifying spillover effects through correlated trading strategies and momentum effects.

Network externality theory explains technology sector's unique volatility patterns, where product utility increases with user adoption (Katz & Shapiro, 1985). This creates strategic complementarities within technology ecosystems, where success or failure cascades through networks via positive feedback loops and tipping point dynamics, particularly in platform-based businesses. Information processing challenges arise from rapid technological change and high uncertainty regarding future cash flows, large R&D expenses, and network-dependent business models (Hall, 2002). These conditions create information asymmetries between stakeholders, leading to systematic mispricing and volatility amplification when investors struggle to distinguish idiosyncratic from systematic factors.

Traditional asset pricing models like CAPM and multi-factor extensions may require adaptation for technology firms' unique risk exposures, including interest rate sensitivity, innovation risk, and ecosystem-specific factors (Fama & French, 1993). Real options theory becomes particularly relevant as technology companies exhibit option-like payoff structures due to R&D investments and platform development opportunities (Schwartz & Moon, 2000), creating high sensitivity to volatility changes and systematic correlations across firms facing similar technological uncertainties. Technology markets experience contagion through mechanisms differing from traditional sectors: portfolio rebalancing treating technology stocks as a single asset class, margin calls during stress, and information cascades where price movements signal broader market conditions (Dornbusch et al., 2000). Ecosystem-specific channels, including platform disruption effects and competitive repositioning, amplify transmission, particularly during market stress periods.

2.3 Empirical Evidence on Volatility Spillovers

Early empirical studies established fundamental patterns of volatility spillovers using correlation and vector autoregression modelling. Hamao et al. (1990) documented substantial volatility spillovers across international stock markets, demonstrating that volatility in one market could predict volatility in another even when controlling for country-specific factors. This pioneering work established that volatility spillovers require specialized econometric models rather than conventional approaches, particularly relevant for technology sectors with high informational flows and complex interdependencies.

Sectoral volatility spillover research reveals industry-specific transmission networks with unique characteristics. Marobhe and Kansheba (2022) examined asymmetrical volatility spillovers in the hospitality sector during COVID-19, documenting significant spillover effects that varied across sub-sectors and highlighting how crisis periods fundamentally alter spillover patterns as weak connections become strong transmission channels during stress. This research underscores the importance of time-varying methods in spillover analysis, as fixed models may fail to capture dynamic relationships across different market regimes. Structural break research provides insights into time-varying spillover patterns. Malik (2021) investigated volatility spillovers among sector equity returns, reporting strong effects of structural breaks on spillover patterns and showing that technology-sector volatility is particularly sensitive to regime shifts due to exposure to technological disruption and changing regulatory environments. The analysis demonstrated that ignoring structural breaks can lead to false conclusions regarding spillover strength and direction.

Pro-cyclical sector studies document particularly strong volatility spillovers. Majumder and Nag (2017) examined shock and volatility spillovers across equity sectors in India's National Stock Exchange, finding two-way volatility spillovers within pro-cyclical domains including Finance and Information Technology. Their IT sector analysis showed increased interconnectedness, suggesting technology firms are more responsive to cross-firm volatility transmission than other sectors, with significant shares of volatility forecasting error variances attributable to spillovers from other technology firms. Cryptocurrency research provides insights into technology-adjacent markets. Vardar and Aydogan (2019) explored the return-volatility nexus between Bitcoin and various asset classes in Turkey, finding notable spillovers from energy and technology stocks to Bitcoin. This reveals complex interconnectedness in technology-related markets and highlights how traditional technology companies drive volatility in emerging digital asset markets.

Cross-country studies reveal the international nature of technology sector spillovers. Balli et al. (2015) found volatility spillovers across Australian industries triggered by global and industrial shocks, demonstrating that technology industries are highly sensitive to international events due to globalization and multinational technology firm operations. Technology sector spillovers often cross national borders, reflecting the global organization of technology markets and multinational operations of dominant firms. The COVID-19 pandemic provided unique insights into spillover effects under extreme market disruption. Vo (2023) noted that intersectoral interconnections were enhanced during this period, facilitating external shock propagation and volatility escalation. Technology companies functioned as both transmitters and receivers of shocks, with varying effects based on business model differences and market segment exposure. Crisis-specific research documents regime-dependent transmission patterns. Guru and Das (2021) measured volatility spillover triggers in Indian stock markets during COVID-19, observing that crises rewired spillover networks with technology companies playing central roles in transmission processes. Technology company spillover behaviour during crises differs substantially from normal times, showing increased bidirectional spillovers and network effects.

The literature demonstrates clear empirical regularities relevant to technology sector analysis. Spillover effects are significantly stronger within sectors than across sectors, highlighting industry-specific determinants. Spillover patterns exhibit considerable time variability, with crisis periods altering intensity and transmission direction. Technology-related sectors consistently demonstrate strong spillover effects as both transmitters and receivers. Regime shifts and structural breaks can fundamentally alter spillover relationships, emphasizing the need for flexible econometric methods that accommodate parameter instability and capture the fundamental uncertainty characteristic of rapidly evolving technology markets.

3. Methodology

3.1 Data and Sampling

This study examines daily natural log returns for nine major US technology companies selected based on systematic criteria to ensure comprehensive representation of the technology sector's leading firms while addressing the theoretical frameworks established in our literature review regarding ecosystem interdependencies and platform economics. Our sample represents four distinct technology ecosystem layers based on value chain positioning and interdependency structures (Jacobides et al., 2018): (1) Platform Infrastructure (Microsoft, Google, Amazon) - core infrastructure providers whose services enable ecosystem participants, creating systematic dependencies consistent with platform economics theory and network externality effects; (2) Consumer Interface (Apple, Meta) - firms controlling user access points and data flows representing the behavioral linkage mechanisms discussed in our theoretical framework; (3) Hardware Foundation (Intel, Nvidia) - semiconductor providers creating supply-side dependencies that operationalize the fundamental linkages described in information transmission theory; and (4) Convergence Sectors (Tesla, IBM) - representatives of technology's expansion into traditional industries and enterprise transformation capturing the structural evolution regarding technology sector characteristics. This framework addresses technology market convergence where traditional sector classifications fail to capture actual interdependencies while providing empirical operationalization of the ecosystem theory and network externality concepts established in our theoretical foundation. The companies are Apple (AAPL), Amazon (AMZN), Google/Alphabet (GOOG), IBM (IBM), Intel (INTC), Meta (META), Microsoft (MSFT), Nvidia (NVDA), and Tesla (TSLA). This ecosystem representation enables analysis of cross-layer volatility transmission patterns that sector-specific studies cannot capture, with each firm maintaining top-50 US market capitalization, ensuring sufficient systemic importance for meaningful spillover analysis while addressing the market concentration concerns and providing empirical grounding for the systemic risk implications discussed in our literature review.

Our sampling approach directly addresses key limitations identified in existing volatility spillover literature by moving beyond traditional sector-based classifications to ecosystem-functional groupings that better capture the interdependency structures theorized in platform economics and network externality literature. Data for these companies were collected from April 1, 2014, to May 31, 2024, sourced from Investing.com, covering critical periods of technology sector evolution, including the platform economy maturation, AI development cycles, and major regulatory developments that characterize the modern technology landscape described in Section 2.1. The natural logarithm of the ratio of consecutive daily closing prices was computed for daily log returns. This transformation normalizes data and stabilizes variance while addressing the unique volatility characteristics of technology firms identified in our theoretical review, particularly their sensitivity to innovation cycles and information asymmetries. As such, this series is now suitable for econometric analysis that accounts for the high-frequency information processing dynamics characteristic of technology markets. Descriptive statistics were computed to describe the distributional properties of log returns with particular attention to the kurtosis and skewness patterns that may reflect the option-like characteristics and network effect dynamics identified in our theoretical framework. To check for stationarity of the log return series, the ADF test was conducted with three specifications: with constant, with constant and trend, and without constant and trend ensuring that our subsequent spillover analysis captures genuine transmission effects rather than spurious correlations arising from non-stationary data.

3.2 Volatility Spillover Analysis

This study is based on the Connectedness Approach, which was developed by Diebold and Yilmaz (2012) and represents the optimal methodological framework for capturing the complex transmission mechanisms identified in our theoretical review, particularly the time-varying nature of technology sector interdependencies. This framework is a follow-up to the seminal work by Diebold and Yilmaz (2009) in measuring volatility spillovers in financial markets using forecast error variance decompositions from VARs. The authors went on to propose measures of directional volatility spillovers in addition to total spillovers, which help identify the sources and recipients of the volatility transmission, thereby providing empirical operationalization of the fundamental, behavioural, and contagion linkages discussed in our information transmission theory framework. The Connectedness Approach contains several main steps that systematically capture the theoretical transmission mechanisms. The first step estimates a time-varying parameter VAR(p) with a rolling window approach, which is particularly suitable for technology markets given their susceptibility to structural breaks and regime changes. Second, H-step-ahead forecast error variance decompositions are calculated from the VAR model to measure the contributions of shocks to the variables in the system.

This step quantifies how much of the future forecast error variance of each variable can be explained by shocks to each variable, including itself, thereby operationalizing the information processing theory and capturing how technology firms' information asymmetries manifest in volatility transmission patterns. The third is the computation of the total connectedness index (TCI) that captures the overall volatility transmission among the firms. The TCI aggregates the forecast error variance contributions and measures the spillover effect within the system, providing an empirical measurement of the ecosystem-level interdependencies theorized in our platform economics and network externality framework.

Fourth, the total directional connectedness measures—total directional connectedness from others and total directional connectedness to others indicate the primary transmitters and receivers of shocks to volatility, respectively, thereby empirically identifying the hub-and-spoke patterns predicted by platform economics theory and the hierarchical structures implied by ecosystem positioning. Fifth, the net total directional connectedness (NET) is calculated. This measure represents the difference between TO and FROM values, indicating whether a company is a net transmitter or net receiver of volatility. A positive NET value means the firm is a net transmitter, and the converse means it is a net receiver providing direct empirical tests of our theoretical predictions regarding platform leaders' roles as volatility transmitters and ecosystem-dependent firms' roles as receivers. The methodology also calculates Net pairwise directional connectedness (NPDC) to measure the directional volatility spillovers for each pair of companies. This allows one to identify the exact relationships and interactions within the network, thereby highlighting the bilateral transmissions of volatilities at the individual level enabling detailed examination of the specific ecosystem relationships and competitive dynamics discussed in our theoretical framework. The Connectedness Approach framework provides a complete study of volatility spillovers concerning overall connectedness, direction of spillovers, and specific pairwise relationships between companies while systematically addressing the theoretical mechanisms identified in Sections 2.1-2.3. This methodology is particularly suitable for technology sector analysis as it captures the time-varying nature of relationships in rapidly evolving markets and accommodates potential feedback loops within the system directly addressing the dynamic characteristics of technology markets identified in our literature review, including innovation cycles, regulatory changes, and platform evolution.

Importantly, our methodological approach addresses key limitations in existing volatility spillover literature by incorporating ecosystem-based theoretical grounding rather than treating technology firms as homogeneous entities. While our directional connectedness measures indicate the direction and magnitude of information flow between firms, they represent statistical associations in variance decompositions rather than causal relationships. The TO and FROM indicators capture how much of one firm's forecast error variance can be explained by shocks to other firms, but this does not establish that one firm's actions directly cause changes in another firm's volatility. Our analysis identifies patterns of information transmission and statistical interdependence, which may reflect underlying economic relationships but should not be interpreted as definitive evidence of causation (Diebold & Yılmaz, 2014) while recognizing that these statistical associations may reflect the theoretical transmission mechanisms identified in our literature review, including platform dependencies, ecosystem complementarities, and network effects.

For our TVP-VAR model implementation, we selected an optimal lag length of 2 based on the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), balancing information retention with model parsimony while ensuring adequate capture of the information processing dynamics characteristic of technology markets discussed in Section 2.2.

The TVP-VAR approach was preferred over alternatives such as DCC-GARCH models due to its superior ability to capture time-varying relationships in financial markets characterized by structural changes (Antonakakis et al., 2020) particularly relevant for technology markets given their exposure to innovation cycles, regulatory changes, and platform evolution documented in our literature review. Furthermore, the TVP-VAR framework better accommodates non-linear dynamics (Maghyereh et al., 2024) that are prevalent in technology markets, particularly during periods of market turbulence such as the COVID-19 pandemic (Dsouza et al., 2024) addressing the regime-dependent behavior and crisis amplification effects identified in Section 2.3 of our empirical literature review. This methodological choice directly addresses the theoretical prediction that technology sector spillovers may exhibit threshold effects, regime-switching behavior, and non-linear feedback loops due to network externalities and platform competition dynamics discussed in our theoretical framework.

To ensure the reliability of our findings, we conducted several robustness checks that address potential concerns regarding the stability of spillover patterns in rapidly evolving technology markets. First, we tested alternative lag specifications ($p = 1$ and $p = 3$) and found that our main results remained qualitatively unchanged confirming that our ecosystem-based transmission patterns are not artifacts of specific model parameterization. Second, we employed different rolling window sizes (150 and 250 days) to verify that our findings were not sensitive to the specific window length chosen for analysis ensuring that our results capture genuine ecosystem relationships rather than temporary market conditions. These sensitivity analyses confirmed the stability of our main findings, indicating that the identified volatility spillover patterns are robust to various model specifications and consistent with the theoretical prediction that ecosystem-based interdependencies should exhibit persistence over different time horizons and model specifications. Our robustness testing framework specifically addresses the concern raised in Section 2.3 regarding the importance of accounting for structural instability and parameter variation in technology sector analysis, while ensuring that our ecosystem-based theoretical predictions are empirically validated across different methodological specifications. All empirical analyses were conducted using R statistical software (version 4.2.1). The TVP-VAR estimation and connectedness measures were implemented using the 'ConnectednessApproach' package providing replicable and transparent implementation of our theoretical framework through established econometric procedures.

4. Findings and Discussion

4.1 Descriptive Analysis

The time-series analysis in the daily natural log returns of the top nine major US technology companies illustrates unique volatility patterns, experiencing different market dynamics and being influenced from the outside. As shown in Figure 1, Tesla exhibits the highest level of fluctuation, which is confirmed by its standard deviation of 0.035 (see Table 1). This high volatility is indicative of Tesla's aggressive market movements and investor speculation during rapid growth phases, particularly from 2018 to 2021. Also, Nvidia has very high volatility with a standard deviation of 0.030, which is related to the firm focusing on AI and gaming; it is clearly seen in rising spikes of returns. IBM has the lowest volatility, with a standard deviation of 0.015, and this would indicate more or less acceptable stability due to its strong market position and conservative investments, in line with the relatively minor spread in Figure 1. Compare this with Meta, which has large deviations, as evidenced by the very high kurtosis of 24.485, indicative of plenty of high deviations, corresponding with the irregularly high spikes on its log return graph in various parts, particularly around significant market events such as the COVID-19 pandemic.

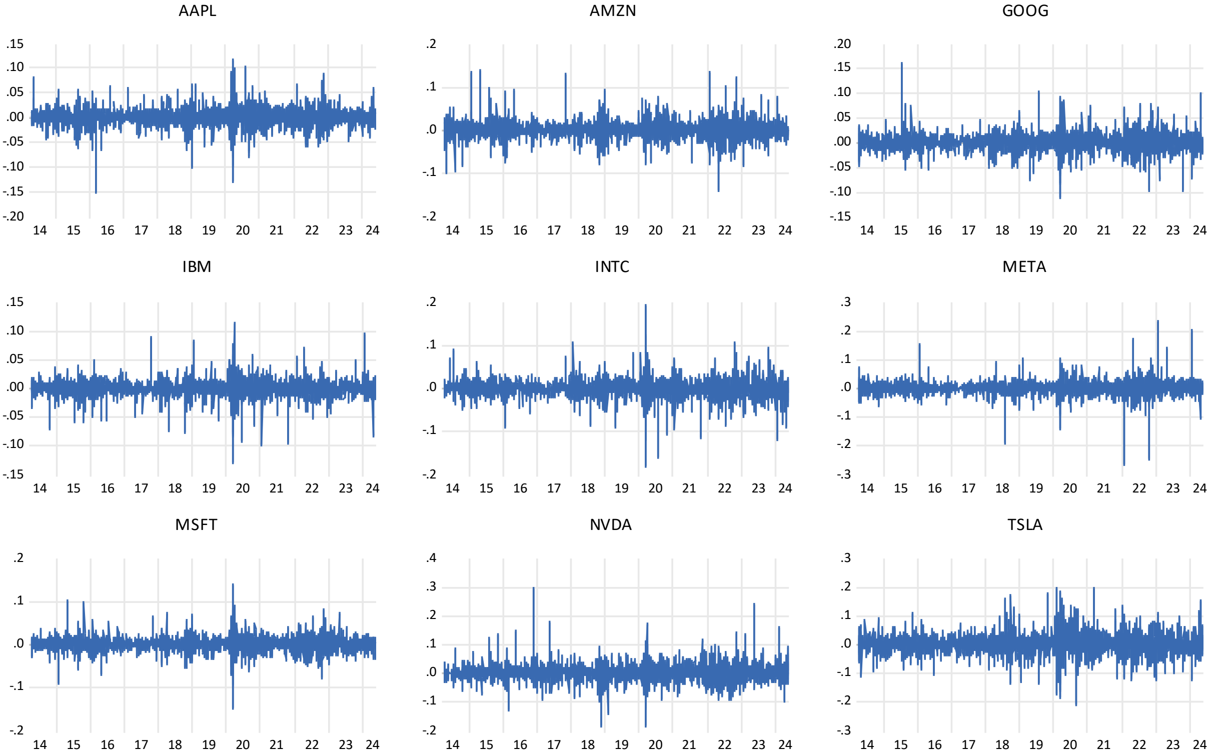

Figure 1: Trend Analysis

For Nvidia, skewness is notably positive at 0.660, meaning the distribution has an extended right tail, indicating a higher likelihood of extreme positive returns compared to a normal distribution. This aligns with sporadic high positive spikes visible in Figure 1. On the other hand, IBM shows a skewness of -0.420, indicating a longer left tail with a higher propensity for extreme negative returns relative to positive ones, suggesting heightened downside risk compared to other companies in the sample. Google has a skewness of 0.280, suggesting moderate asymmetry toward positive returns. Tesla and Nvidia exhibit the highest volatility, as evidenced by their standard deviations of 0.035 and 0.030, respectively. This heightened volatility reflects larger daily price swings and is characteristic of high-growth technology firms with significant AI investments, consistent with findings from Gharbi et al. (2014), who documented similar patterns in innovative technology stocks. These observations are essential in the context of understanding volatility spillovers in the AI-driven technology market. The mean and median returns for most companies are close to zero, indicating marginal average daily returns over the period, while Nvidia (0.003) and Tesla (0.002) show marginally higher mean returns, demonstrating relatively better performance on average. Furthermore, Meta exhibits the most extreme price movements with the highest maximum return of 0.233 and the most negative minimum return of -0.264, indicating very significant fluctuations. These extreme values are supported by Meta's exceptionally high kurtosis of 24.485, indicating a leptokurtic distribution with heavy tails that makes extreme returns more probable than in a normal distribution.

4.2 Unit Root Analysis

As Table 2, in all three different specifications of the ADF test, daily log returns for all nine major US technology companies are found to be stationary. This lends robustness to the whole exercise as evidence against a unit root in the log return series. So, these series are stationary, implying that necessary statistical properties like mean and variance remain unchanged in the long run, thus making them suitable for furthering econometrical modeling and analysis.

Table 1: Unit Root Test Results Table (ADF -At Level)

		AAPL	AMZN	GOOG	IBM	INTC	META	MSFT	NVDA	TSLA
With Constant	t-Statistic	-16.046	-51.217	-17.805	-15.904	-11.940	-17.632	-17.669	-18.025	-50.711
	Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
With Constant & Trend	t-Statistic	-16.043	-51.219	-17.807	-15.937	-14.305	-17.629	-17.665	-18.051	-50.703
	Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Without Constant & Trend	t-Statistic	-15.762	-51.075	-17.527	-15.906	-11.919	-9.875	-17.175	-15.958	-27.857
	Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

4.3 Total Connectedness Analysis

Figure 2 depicts the Total Connectedness Index (TCI) showing substantial fluctuations that reflect varying degrees of interconnectivity among nine major US technology firms, providing empirical validation of the time-varying nature of technology sector interdependencies predicted by our theoretical framework, particularly the regime-dependent behavior. At the start of the observed period (2016), the TCI shows high interconnectedness, potentially reflecting earlier platform ecosystem maturation theorized in literature. Notable peaks occur in 2016, 2018, 2020, and 2022, with 2020 representing the most prominent spike corresponding to the COVID-19 pandemic onset. The 2016 peak coincides with Brexit referendum uncertainty and US presidential election volatility affecting global technology markets, while the 2018 spike corresponds to US-China trade war escalation and technology sector tariff concerns, demonstrating how geopolitical events amplify technological interdependencies theorized in our framework. The 2020 peak emphasizes increased interconnectivity during the pandemic as stock return shocks across companies had considerably significant effects on each other, indicating heightened systemic risk and market uncertainty, thereby providing empirical validation of contagion theory predictions, where crisis periods amplify fundamental interdependencies through behavioral and liquidity channels. Post-2020, interconnectedness decreases as the TCI drops, revealing market stabilization. The 2022 peak corresponds to Federal Reserve interest rate increases and technology sector earnings disappointments, reflecting the sector's sensitivity to macroeconomic conditions theorized in our asset pricing framework. Post-2022 volatility indicates fluctuating interconnectivity, potentially driven by technological developments, market events, or external shocks to the technology sector, confirming the dynamic nature of ecosystem interdependencies and validating our theoretical prediction that technology sector spillovers exhibit time-varying intensity corresponding to innovation cycles and external shocks.

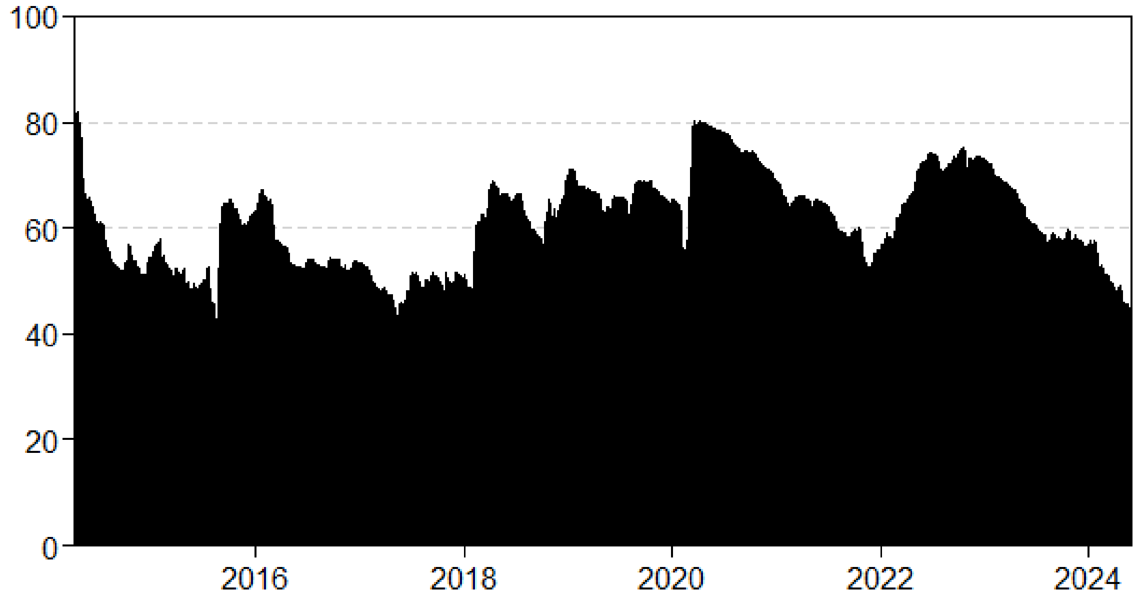

Figure 2: Total Connectedness Index (TCI)

4.4 Directional Connectedness Analysis

Figure 3 shows the total directional connectedness TO others (TOi) for nine major US technology companies, measuring each firm's influence on all other series and demonstrating individual company impact within this network, thereby providing direct empirical tests of our theoretical predictions regarding ecosystem hierarchy and platform leadership roles. The figure reveals varying degrees of influence among companies over time, consistent with our ecosystem-based theoretical framework predicting systematic differences in transmission roles across functional layers. Apple (AAPL), Amazon (AMZN), Google (GOOG), Microsoft (MSFT), and Nvidia (NVDA) exhibit the highest total directional connectedness TO others, indicating the most influence on other firms, consistent with theoretical expectations that platform infrastructure and consumer interface firms would emerge as dominant transmitters due to their central positions in the technology ecosystem. These companies show elevated TOi values during critical market events and increased volatility periods, such as the COVID-19 pandemic around 2020, suggesting patterns consistent with crisis amplification effects predicted by contagion theory and behavioral finance frameworks. Microsoft (MSFT) exhibits persistently high TOi values relative to peers, reflecting a stable transmission role in the technology market and aligning with platform economics theory that infrastructure providers with extensive ecosystem dependencies would consistently emerge as volatility transmitters. Similarly, Google (GOOG) and Apple (AAPL) demonstrate substantial influence, with their TOi values peaking during market turbulence periods, consistent with theoretical predictions about platform leaders' roles in information transmission and ecosystem coordination. Nvidia's (NVDA) post-2020 TOi surge reflects its growing AI ecosystem dominance, while Amazon's (AMZN) consistent high influence confirms multi-platform operators as systemic transmission nodes, validating our ecosystem framework's prediction that hardware foundation and multi-platform operators would exhibit significant transmission capacity due to their critical positions in technology value chains. IBM (IBM) and Intel (INTC) show the most limited TOi scores, indicating least influence on other companies, empirically consistent with our theoretical prediction that convergence sector and cyclical hardware firms would exhibit limited transmission capacity due to their dependent positions within the broader technology ecosystem. Meta (META) demonstrates intermediate influence with notable increases during specific market stress periods, reflecting the consumer interface layer's intermediate position and exposure to regulatory and competitive pressures theorized in our framework.

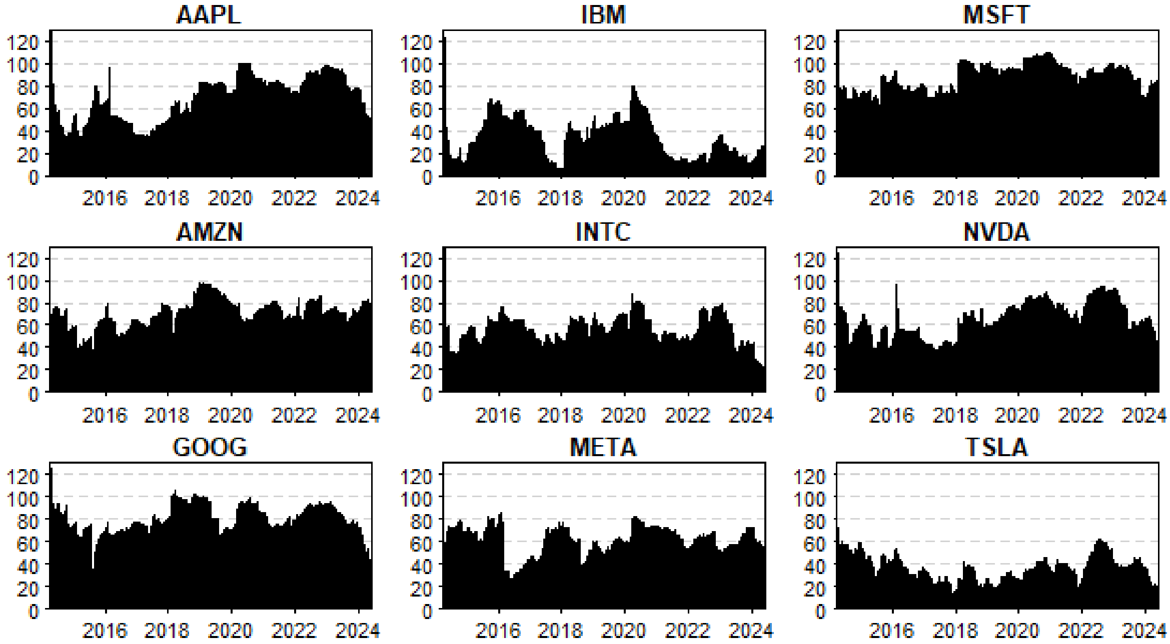

Figure 3: Total directional connectedness-TO

Figure 4 shows the total directional connectedness FROM others (FROMi) measuring how much shock in each company's stock comes from others, providing empirical validation of theoretical predictions regarding ecosystem vulnerability patterns. IBM and Intel exhibit consistently higher FROMi values, indicating greater vulnerability to external market movements with peaks during crises such as the 2020 pandemic. This pattern aligns with resource dependence theory (Pfeffer & Salancik, 1978), where firms in mature or cyclical technology segments become more susceptible to ecosystem-wide developments, with IBM's vulnerability reflecting dependence on enterprise technology adoption cycles and Intel's sensitivity stemming from exposure to demand fluctuations across multiple semiconductor-driving technology segments. In contrast, Apple, Google, and Microsoft exhibit the lowest FROMi values, demonstrating relative insulation from external shocks. This validates platform economics theory (Parker et al., 2017), where ecosystem orchestrators with control over critical infrastructure and user networks possess structural advantages that buffer external volatility while maintaining influence over dependent firms. Nvidia maintains moderate FROMi despite its AI infrastructure role, reflecting specialized semiconductor applications that partially insulate it from broader technology cycles while maintaining supply chain dependencies, providing nuanced evidence of hardware foundation firms' complex positioning that challenges simple theoretical predictions. Tesla shows higher vulnerability reflecting electric-vehicle supply-chain dependencies. Amazon and Meta exhibit high sensitivity with significant increases during market disruptions. Their higher-than-expected sensitivity challenges platform economics predictions, with Amazon's exposure to multiple business cycles simultaneously (retail, cloud, logistics) and Meta's dependence on advertising markets and regulatory environments creating vulnerabilities despite network advantages, demonstrating that business model complexity and regulatory exposure can override platform characteristics in determining transmission patterns and highlighting the need for theoretical frameworks accounting for multi-dimensional risk exposures.

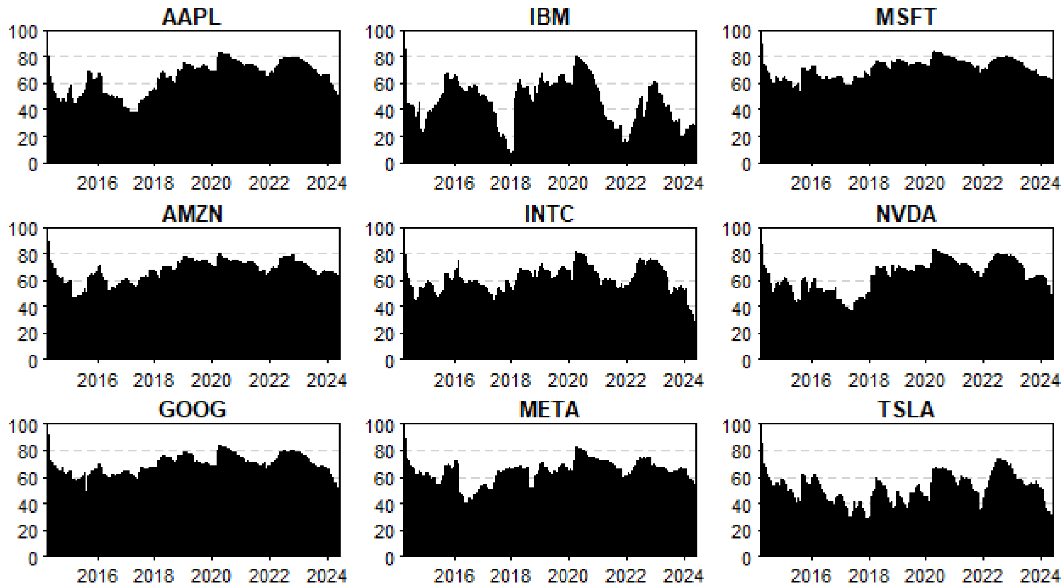

Figure 4: Total Directional Connectedness- FROM

Figure 5 shows the net total directional connectedness (NETi) measuring whether firms are net transmitters (NETi > 0) or receivers (NETi < 0) of shocks, providing comprehensive empirical validation of our ecosystem-based theoretical framework's transmission hierarchy predictions. Microsoft (MSFT), Google (GOOG), and Apple (AAPL) exhibit consistently positive NETi values, confirming their roles as net transmitters and ecosystem orchestrators with significant network impact. Microsoft shows particularly strong positive NETi, highlighting its role as a major market influencer and empirically validating platform economics theory predictions regarding platform leaders' systemic volatility transmission capabilities. IBM and Intel (INTC) are characterized by negative NETi values as net receivers, responding to market shocks rather than causing them, providing empirical validation of resource dependence theory predictions regarding convergence and cyclical hardware firms' vulnerable positions within technology ecosystems. Amazon (AMZN), Meta (META), Nvidia (NVDA), and Tesla (TSLA) display oscillating NETi values, transitioning between net transmitter and receiver roles. This variability reflects regime-dependent transmission characteristics, with AMZN/META's business model complexity (e-commerce/advertising exposure combined with platform elements) and NVDA/TSLA's innovation cycle dependencies (AI leadership and supply-chain exposures respectively) creating time-varying transmission capacities. These patterns empirically demonstrate the dynamic nature of ecosystem relationships and confirm our theoretical prediction that firms' positions within transmission networks exhibit time-varying characteristics corresponding to market conditions and ecosystem evolution, thereby validating the value of ecosystem-based approaches to understanding technology sector interdependencies and providing empirical foundation for theoretical frameworks established in our literature review.

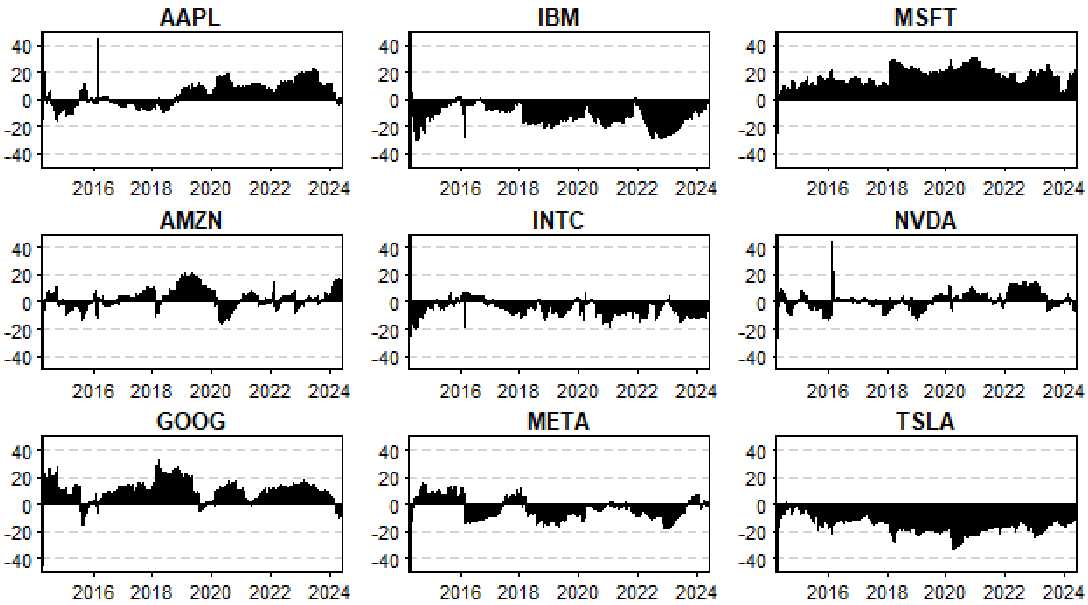

Figure 5: Net Total Directional Connectedness (NETi)

4.5 Network Structure Analysis

The spillover dynamics revealed from Table 3 and Figure 6's network plot provide comprehensive empirical validation of our theoretical framework's ecosystem-based interdependency predictions. MSFT and GOOG emerge as dominant transmitters with TO values of 86.47 and 78.67 respectively, confirming platform economics theory where ecosystem dependencies amplify volatility transmission through Azure/Office infrastructure (MSFT) and search/advertising/cloud foundational positions (GOOG), thereby providing direct empirical validation of theoretical mechanisms regarding platform economics and network externalities as transmission amplifiers. Figure 6's network visualization reveals a core-periphery structure where node size represents market influence and edge thickness indicates transmission strength, with leading tech giants forming central hubs with thick outgoing edges, validating ecosystem theory predictions about hierarchical transmission channels where infrastructure providers occupy central positions due to their foundational market roles. This clustering pattern demonstrates volatility concentration around major technology platform providers rather than even distribution across the sector, indicating platform ecosystem leadership correlates with systemic importance and providing empirical evidence for systemic risk implications theorized in Section 2.1. Apple (AAPL) and Amazon (AMZN) serve as notable net transmitters with TO values of 67.77-68.59, confirming their roles as consumer interface controllers and multi-platform operators whose market decisions correlate with adoption patterns across multiple technology segments. Nvidia (NVDA) with TO value of 63.53 reflects its critical AI and gaming value chain position where semiconductor innovations correlate with performance expectations across dependent industries, validating theoretical predictions regarding hardware foundation firms' transmission capacity through innovation spillovers. In contrast, IBM and Tesla are net receivers with high FROM values of 44.52 and 49.34 respectively, with IBM's status aligning with resource dependence theory where mature enterprise segments exhibit sensitivity to platform leaders' shifts, while Tesla demonstrates convergence firms' statistical associations with core technology infrastructure despite market prominence. Intel (INTC) and Meta (META) similarly function as net receivers with FROM values of 59.27 and 63.36, reflecting cyclical semiconductor associations with ecosystem demand patterns (Intel) and social media platforms' sensitivity to broader technology infrastructure and regulatory developments (Meta), providing empirical evidence for complex interdependencies while highlighting how consumer interface firms can exhibit receiver characteristics under specific market conditions.

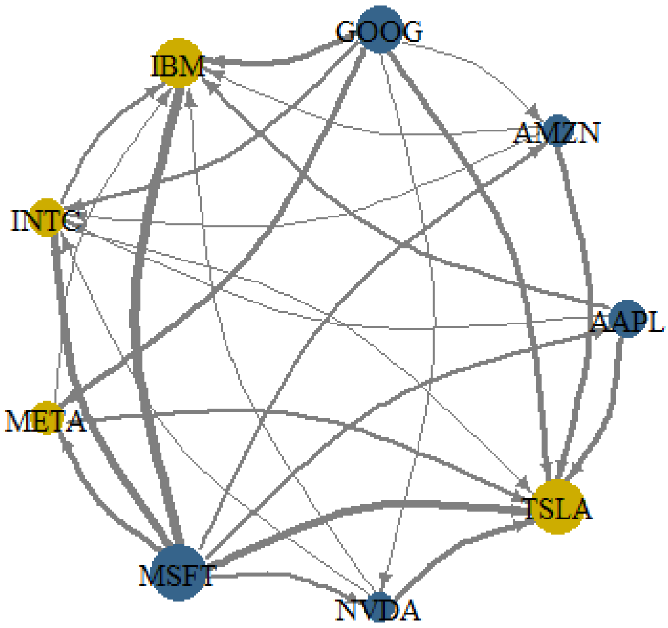

Figure 6: Network Plot of Net Pairwise Directional Connectedness (NPDC)

The matrix reveals directional pairwise connectedness in the volatility network, representing statistical relationships rather than causal mechanisms. Figure 6's visualization shows Microsoft (TO: 86.47, NET: +16.36) and Google (TO: 78.67, NET: +10.19) as dominant net transmitters (blue nodes), while Tesla (NET: -14.96) and IBM (NET: -12.09) emerge as primary net receivers (yellow nodes). The core-periphery structure demonstrates that platform infrastructure providers (MSFT/GOOG) occupy central positions with thick outgoing edges, while dependent firms (TSLA/IBM) remain peripheral. Notably, IBM transmits more volatility to Google (6.45) than Google transmits to IBM (4.12), illustrating complex directional relationships that challenge simple platform hierarchy assumptions. Microsoft's cloud infrastructure and enterprise ecosystem dependencies, combined with Google's foundational search/advertising/cloud positions, amplify their transmission capacity through platform-based business models. Tesla's net receiver status despite substantial market capitalization demonstrates that ecosystem positioning and business model characteristics determine network roles rather than market size alone, validating our theoretical framework's emphasis on functional roles over simple size metrics. The Total Connectedness Index of 60.81% indicates moderate system-wide connectedness, with significant risk management implications for net receivers who show greater vulnerability to externally-originated volatility shocks.

The NETi measurements show Microsoft (+16.36) and Google (+10.19) as substantial net volatility exporters, with Tesla (-14.96) and IBM (-12.09) as significant net importers. These asymmetric patterns align with information processing theory (Grossman & Stiglitz, 1980), where platform leaders with superior information access influence price discovery for information-dependent firms, confirming that ecosystem positioning determines transmission hierarchy more than market size alone. External factors amplify these transmission patterns, as evidenced by increased interconnectedness during COVID-19, suggesting macroeconomic shocks intensify existing channels rather than altering network structure. This supports contagion theory (Forbes & Rigobon, 2002), where crises amplify fundamental interdependencies while preserving underlying architecture. Geopolitical tensions correlate with differential volatility patterns, where supply-chain-dependent firms like Intel (NET: -4.79) show higher shock absorption reflecting embedded volatility from Asian semiconductor supply chains, contrasting with cloud-centric digital models, though unobserved confounders may contribute to these patterns. The dense interconnections validate ecosystem theory predictions (Moore, 2006) about technological interdependencies creating systematic transmission channels, with directional asymmetries like Microsoft→Tesla (7.30) versus Tesla→Microsoft (4.36) confirming resource dependence theory where firms controlling critical resources exert disproportionate influence over dependent firms. However, IBM's notable spillover to Google (6.45) demonstrates that legacy firms can retain influence in specific relationships despite overall high receptiveness (FROM: 44.52), adding complexity to simple platform hierarchy assumptions. Apple's moderate net transmitter role (+4.76) and high receptiveness (FROM: 63.02) reflect its hybrid position as a platform leader with significant exposure to consumer demand shocks. These results establish Microsoft and Google as primary focal points for monitoring market volatility and systemic risk, though underlying causal mechanisms require investigation through alternative methodological approaches while providing empirical foundation consistent with theoretical frameworks established in our literature review.

Table 2: Diebold and Yilmaz connectedness matrix

	AAPL	AMZN	GOOG	IBM	INTC	META	MSFT	NVDA	TSLA	FROM
AAPL	36.98	8.12	9.11	3.83	6.41	7.54	11.03	12.05	4.93	63.02
AMZN	8.38	33.92	13.24	3.08	5.28	10.8	12.38	7.64	5.28	66.08
GOOG	8.58	12.2	31.52	4.12	6.31	11.16	14.36	7.65	4.1	68.48
IBM	5.51	4.34	6.45	55.48	9.02	3.66	8.59	4.39	2.56	44.52
INTC	7.7	6.18	7.88	7.31	40.73	5.67	11.95	8.68	3.9	59.27
META	8.22	11.52	13.22	2.7	5.28	36.64	10.34	7.08	5.01	63.36
MSFT	9.62	10.91	13.6	5.34	9.3	8.21	29.89	8.78	4.36	70.11
NVDA	12.42	7.92	8.58	3.25	7.85	6.65	10.51	37.75	5.05	62.25
TSLA	7.34	7.41	6.59	2.8	5.04	6.41	7.3	7.26	49.84	50.16
TO	67.77	68.59	78.67	32.43	54.48	60.11	86.47	63.53	35.19	547.25
Inc.Own	104.76	102.51	110.19	87.91	95.21	96.75	116.36	101.29	85.04	cTCI/TCI
NET	4.76	2.51	10.19	-12.09	-4.79	-3.25	16.36	1.29	-14.96	68.41/60.81
NPT	6	5	7	1	2	3	8	4	0	

5. Conclusion

This paper extensively examines volatility spillover of nine of the most major United States technology corporations through the perspective of ecosystem-based framework and Connectedness Approach methodology. This analysis captures the trend of interdependence and the influence of volatilities of stock returns of these companies, and thus aids in enhancing the knowledge on the current trends of modern technology market dynamics. The empirical findings reveal that there are different volatility profiles reflecting the unique position of each of the companies in the technological ecosystem. Tesla and Nvidia record the highest levels of volatility due to the active movements in the market and high levels of investor speculations in the days of significant growth. Conversely, IBM has the least volatility, which means that its performance is more or less constant on account of its market presence. The substantial fluctuations in Meta, which is marked by high kurtosis, is associated with key market occurrences, especially the COVID-19 pandemic, thus demonstrating the extent of external provocations highlighting the impact of external shocks.

The Total Connectedness Index (TCI) has significant temporal variation, whereby its peaks reflect salient market events like the COVID-19 pandemic, the 2016 Brexit/election uncertainty, the 2018 trade war tensions, and the 2022 Federal Reserve policy shifts. These variations confirm the hypothesis that the volatility spillovers are increased during the periods of crisis due to the increased uncertainty of the investors, as well as to the increased likelihood of correlated trading. The directional connectedness analysis establishes that the volatility connection is significant at the technology sector level with a few companies, Microsoft, Google, Apple, Amazon, and Nvidia being the chief transmitters that influence other companies considerably. This transmission hierarchy aligns with platform economics theory, where infrastructure providers and ecosystem orchestrators naturally become volatility sources due to their central positions in value networks. Conversely, IBM and Intel emerge as net receivers, indicating greater susceptibility to external market movements consistent with their dependent positions within technology ecosystems. The net pairwise directional connectedness analysis confirms Microsoft and Google as dominant transmitters, while IBM and Tesla are primary receivers, demonstrating that ecosystem positioning rather than market capitalization determines transmission hierarchy.

Understanding spill over patterns among the top technology firms provides key information to a wide range of stakeholders. For investors, implementing asymmetric hedging programs, which take into consideration the directional transfer of volatility, will provide a more effective protection to the portfolio. Portfolios exposed to receiver firms such as IBM and Intel can obtain superior protection by taking protective positions on transmitters Microsoft and Google, rather than hedging directly. Early warning systems based on the release of strategic announcements by key transmitters can inform investment and risk management decisions. For regulatory bodies, identifying systemically important firms enables targeted oversight frameworks. Stress testing should specifically simulate shocks originating at core transmission points, especially Microsoft and Google, and regulatory frameworks should explicitly recognize the systemic importance of technology platform providers to reduce the exposure to concentration risk effectively. For corporations, receiver firms ought to set up monitoring systems for strategic changes by key transmitters and deploy counter-cyclical measures to reduce vulnerability. Understanding the patterns of transmission enables the firms to calibrate strategic decisions to market conditions, by seeking growth when the inter connectedness is low and being cautious when it is high pursuing growth during low interconnectedness periods and exercising caution during heightened transmission phases.

Our connectedness measures represent statistical associations rather than causal relationships, requiring future research using instrumental variables or structural models to establish definitive causality. Focusing on nine major firms may miss dynamics from smaller or emerging technology companies, potentially limiting understanding of broader market interdependencies. The US-centric analysis may not capture global interdependencies and international spillovers. Future research should expand the sample to include smaller technology firms and international markets for more comprehensive understanding. Incorporating sector-specific variables such as R&D intensity, platform ecosystem metrics, and regulatory environment indicators could better capture unique characteristics driving technology sector spillovers. These extensions would provide more robust insights for investors, policymakers, and industry stakeholders.

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