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Volatility Spillovers among Major U.S. Companies

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Abstract:

Purpose: *Volatility spillovers among leading U.S. companies have important implications for portfolio diversification, systemic stability, and risk management. The presented study investigated whether technology-driven shocks transmit beyond their own sector to influence consumer and financial firms. Eleven large U.S. companies (AAPL, AMZN, PEP, TSLA, MSFT, META, AVGO, NVDA, ADBE, NDAQ, and GOOGL) were examined in order to identify the size, direction, and significance of firm-to-firm volatility linkages.*
Design/Methodology/Approach: *Daily data covering the period 2015-2024 were used. Returns and thirty-day rolling standard deviations were calculated. Pairwise Granger causality tests were applied to the volatility series. Significant relations were collated into spillover matrices to visualize the propagation of shocks across firms.*
Findings: *Analysis revealed that volatility spillovers are concentrated within the technology sector, with META, MSFT, and NVDA identified as key transmitters. Cross-sector effects were also observed, most notably spillovers from technology into consumer and financial firms such as PEP and NDAQ. These results indicate that sector-based diversification strategies may underestimate true exposure to volatility.*
Practical Implications: *The results may be of interest to investors, risk managers, and policymakers concerned with portfolio construction, stress testing, and systemic risk oversight. The evidence suggests that firm-level spillovers should be explicitly incorporated into investment and regulatory frameworks.*
Originality/Value: *The study contributes to the literature by shifting the spillover analysis from markets and sectors to a firm-level perspective within the U.S. mega-cap universe. The results fill an empirical gap regarding the identification of specific companies that act as volatility transmitters across sectors. The findings provide recommendations for enhancing portfolio risk controls and monitoring systemic vulnerabilities in equity markets.*

Keywords: *Volatility spillover, Granger causality, U.S. equities, network interdependence, portfolio diversification, risk management, technology sector.*

JEL Codes: *C22, G12, G15.*
Paper type: *Research article.*

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1. Introduction

The interconnectedness of financial markets is reflected in the transmission of shocks across firms and sectors and has been widely studied in the literature. Volatility, as a measure of uncertainty, not only captures the risk associated with individual securities but also represents systemic linkages that affect overall market stability (Kumar, 2013; Jebran and Iqbal, 2016; Gamba-Santamaria *et al.,* 2019).

Previous studies documented volatility transmission both within and across equity markets and between equities and other asset classes. For example, Harris and Pisedtasalasai (2006) analyzed return and volatility spillovers between large and small stocks in the UK. Mikhaylov (2018) examined the volatility spillover effect between stock and exchange rates in oil-exporting countries. Malik (2021) investigated volatility interactions between exchange rates and stock returns under volatility shifts. More recently, Khan (2023) reported bidirectional volatility spillovers between India and BRICS countries.

A number of contributions emphasized the intensification of spillovers during crisis episodes. Gamba-Santamaria *et al.* (2019) highlighted that global spillovers peaked during the 2007–2009 financial crisis. Xu *et al.* (2019) confirmed asymmetric volatility spillovers between oil and stock markets in China and the United States. Baruník *et al.* (2016) presented evidence of asymmetric volatility spillovers across U.S. petroleum markets. Furthermore, sectoral studies have demonstrated that technology and consumer-related stocks play a crucial role in transmitting shocks due to their market capitalization and central role in innovation (Geng *et al.,* 2021; BenSaïda *et al.,* 2018).

Despite the breadth of existing research, the firm-level dimension of volatility spillovers within U.S. mega-cap companies has not been explored in sufficient detail. Most studies focus on aggregate indices, cross-country panels, or sectoral groups, while less attention is devoted to identifying which firms act as key transmitters of volatility within the U.S. equity market.

The present study addresses this gap by analyzing volatility spillovers among eleven U.S. firms—AAPL, AMZN, PEP, TSLA, MSFT, META, AVGO, NVDA, ADBE, NDAQ, and GOOGL—covering the period 2015-2024. The analysis is conducted using thirty-day rolling standard deviations of daily returns and pairwise Granger causality tests.

The empirical results are summarized through spillover matrices that highlight the network of statistically significant firm-to-firm linkages. The aim of the article is to identify the companies that serve as transmitters of volatility across and within sectors, and to evaluate the implications of such spillovers for portfolio diversification, systemic stability, and risk management.

2. Literature Review

Research on volatility spillovers has developed extensively over the last two decades, emphasizing both cross-country and sectoral interdependencies. Early studies highlighted that volatility transmission occurs not only within equity markets but also across asset classes. Harris and Pisedtasalasai (2006) documented that volatility of large-cap stocks significantly influences small-cap stocks in the United Kingdom.

Kumar (2013) confirmed strong integration among the IBSA markets, with bi-directional spillovers between stock prices and exchange rates. Korkmaz *et al.* (2012) examined CIVETS countries and observed relatively low but present volatility spillovers, while Mukherjee and Mishra (2010) established the presence of return spillovers between India and its Asian counterparts.

Crisis episodes received special attention in the literature. Gamba-Santamaria et al. (2019) found that global stock market volatility spillovers peaked during the 2007–2009 financial crisis. Baruník *et al.* (2016) identified asymmetric volatility spillovers in U.S. petroleum markets during the same period. BenSaïda *et al.* (2018) confirmed that volatility transmission across global financial markets intensifies in times of instability, whereas Gamba-Santamaria *et al.* (2017) showed that Brazil serves as a primary volatility transmitter to other Latin American markets. Xu *et al.* (2019) extended this perspective by identifying asymmetric volatility spillovers between oil and stock markets in China and the United States.

Recent contributions have focused on sectoral and firm-specific dimensions. Mikhaylov (2018) demonstrated that exchange rates and equities in oil-exporting countries are linked through significant volatility spillovers. Malik (2021) showed that U.S. equity volatility influences exchange rate dynamics. Geng *et al.* (2021) provided evidence of high volatility spillovers in the renewable energy sector, underscoring the role of negative news in amplifying risk. Khan (2023) examined BRICS countries and confirmed bidirectional volatility transmission between India and other emerging markets.

Although the literature demonstrates robust evidence of volatility spillovers across countries, markets, and sectors, relatively little attention has been paid to identifying spillovers at the firm level within the U.S. equity market. Most prior research has focused on aggregate indices or broad sectors, while the transmission of volatility among individual firms—especially U.S. mega-cap companies—remains underexplored.

The present study addresses this gap by investigating firm-level volatility spillovers among eleven major U.S. companies across the technology and consumer sectors, using Granger causality and spillover matrix approaches to identify the main transmitters of volatility within the U.S. market.

Table 1. *Selected studies on volatility spillovers (methods, regions, periods)*

Authors	**Year**	**Region Studied**	**Variables Used**	**Main Finding**	**Method Used**	**Data Period**
Manish Kumar	2013	IBSA (India, Brazil, SA)	Returns & Volatility Spillovers	Strong integration, bi-directional spillovers	VAR, GARCH	2000–2011
Jebran & Iqbal	2016	Asia (Pakistan, India, etc.)	Volatility	Significant bidirectional & unidirectional spillovers	GARCH	1999–2014
Gamba-Santamaria et al.	2019	Global (USA, UK, China, etc.)	Stock Market Volatility	Peak spillovers in 2007–2009 crisis	DCC-GARCH	1996–2017
Mikhaylov	2018	Russia & Brazil	Stock & Exchange Rate	Stronger spillovers post-2009 crisis	FIGARCH	2009–2017
Harris & Pisedtasalasai	2006	UK	Large & Small Stock Volatility	Large stocks predict small stocks	AR-GJR-GARCH-M	1986–2002
Baumöhl et al.	2017	40 Global Markets	Stock Market Volatility	Higher spillovers in nearby markets	Granger Causality	2006–2014
Malik	2021	USA	USD & Stock Market Volatility	US stocks influence USD exchange rate	Bivariate GARCH, ICSS	2003–2018
Korkmaz et al.	2012	CIVETS (Colombia, etc.)	Stock Returns & Volatility	Low spillover, interdependence observed	GARCH, Causality	2002–2010
Xu et al.	2019	China & USA	Oil & Stock Market Volatility	Asymmetric spillovers	Spillover Index	2007–2016
Imran Khan	2023	BRICS	Volatility	Bidirectional spillover between India and BRICS	Granger Causality	2013–2021
Geng et al.	2021	Global (New energy companies)	Return & Volatility Spillovers	High spillovers, negative news contributes to risk	Generalized VAR decomposition	2006–2019
Mukherjee & Mishra	2010	India & Asia	Stock Market Volatility	Bi-directional return spillovers	GARCH, Granger Causality	1997–2008

Imran Khan	2021	Emerging Market	Stock returns	Volatility spillover from India to BRICS	VAR, Granger Causality, DCC-GARCH	2003–2018
Baruník et al.	2016	USA	US Stock Sector Volatility	Asymmetric volatility spillovers	Spillover Index	2004–2011
Ahmed BenSaïda et al.	2018	US, UK, France, etc.	Volatility	Increased spillovers during financial crises	Variance decomposition	2001–2017
Gamba-Santamaria et al.	2017	Latin America & USA	Stock Returns & Volatility	Brazil transmits, others receive spillovers	Spillover Index, DCC-GARCH	2003–2016

Source: *Adapted from Kumar (2013); Jebran & Iqbal (2016); Gamba-Santamaria et al. (2019); Mikhaylov (2018); Harris & Pisedtasalasai (2006); Lyócsa, Výrost & Baumöhl (2019); Korkmaz, Çevik & Atukeren (2012); Xu et al. (2019); Khan (2023); Mukherjee & Mishra (2010); Baruník et al. (2016); Gamba-Santamaria et al. (2017); Malik (2021); BenSaïda et al. (2018); Geng et al. (2021).*

3. Data and Methodology

3.1 Data

The empirical analysis uses daily closing prices for eleven U.S. companies—Apple (AAPL), Amazon (AMZN), Alphabet Class A (GOOGL), Adobe (ADBE), Broadcom (AVGO), Meta Platforms (META), Microsoft (MSFT), Nasdaq (NDAQ), NVIDIA (NVDA), PepsiCo (PEP), and Tesla (TSLA)—sourced from Yahoo Finance.

The sample spans 3 January 2015 to 15 October 2024. Logarithmic returns were computed as $r_t = \ln P_t - \ln P_{t-1}$, yielding 2,462 observations per firm. Volatility was proxied by the thirty-day rolling standard deviation of daily returns, producing 2,461 observations due to the moving window. Descriptive statistics for returns and volatilities are reported in Table 1 and Table 2, respectively.

3.2 Econometric Approach

Pairwise Granger causality tests were applied to the volatility series of each firm pair in order to examine predictive linkages. The null hypothesis states that past values of volatility from firm *i* do not provide additional explanatory power for the volatility of firm *j* beyond the lags of firm *j* itself. Wald χ^2 statistics and corresponding *p*-values were computed, with statistical significance evaluated at the 10% level ($p < 0.10$). To provide a synthetic representation of the results, statistically significant relationships were collated into spillover matrices, where the row firm indicates the volatility transmitter and the column firm denotes the recipient.

Pairwise Granger tests involve many hypotheses. Reported p-values are unadjusted and should be interpreted as exploratory evidence of predictability rather than definitive inference. To reduce over-interpretation, our discussion emphasizes stronger links ($p \le 0.05$), while full results at $p < 0.10$ are reported for transparency.

Lag selection: For each pairwise VAR used in the Granger tests, we evaluated lag lengths $L \in \{1,2,3,4,5\}$ using the Akaike (AIC) and Schwarz/Bayesian (BIC) information criteria on the volatility series. Both criteria selected short lags, with L=2 the modal choice across pairs. To ensure comparability across tests, we fixed the lag length at L=2 for all pairs (yielding Wald tests with df=2).

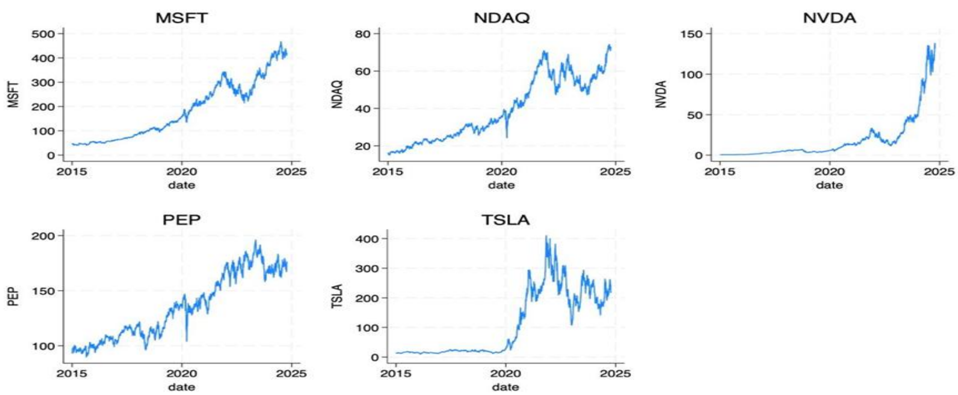
Stationarity and preprocessing: Because rolling-window volatility can be persistent, we tested each volatility series for stationarity using ADF (unit-root null) and KPSS (stationarity null) tests. Prior to estimation, series were standardized to z-scores (demeaned and scaled by their sample standard deviation) to harmonize units across firms. Where ADF/KPSS diagnostics disagreed at the margin, we relied on the joint evidence and confirmed that VAR residuals passed serial-correlation checks

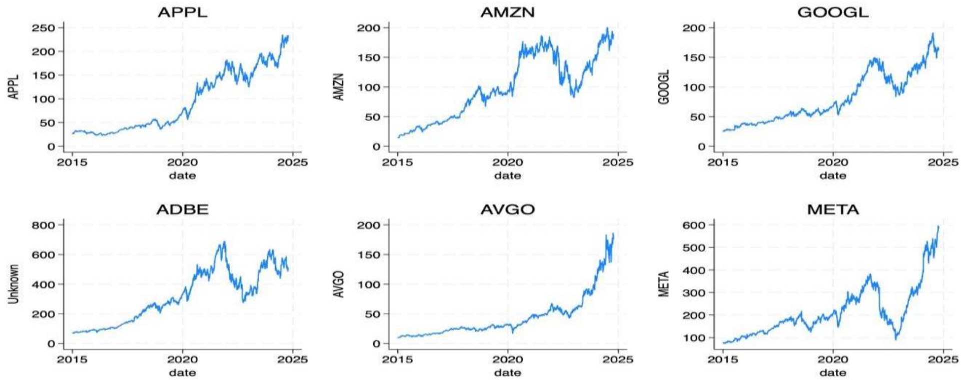
All statistical analyses were conducted in Stata 18 (StataCorp LLC).

4. Empirical Results

The empirical analysis begins with an examination of descriptive statistics and graphical representations of the underlying data. Figures 1-3 present the daily closing prices, logarithmic returns, and thirty-day rolling volatilities for the eleven selected companies over the sample period 2015-2024. The plots illustrate the long-term upward trends in technology stocks, short-term fluctuations in returns with evidence of volatility clustering, and periods of heightened volatility corresponding to episodes of market stress.

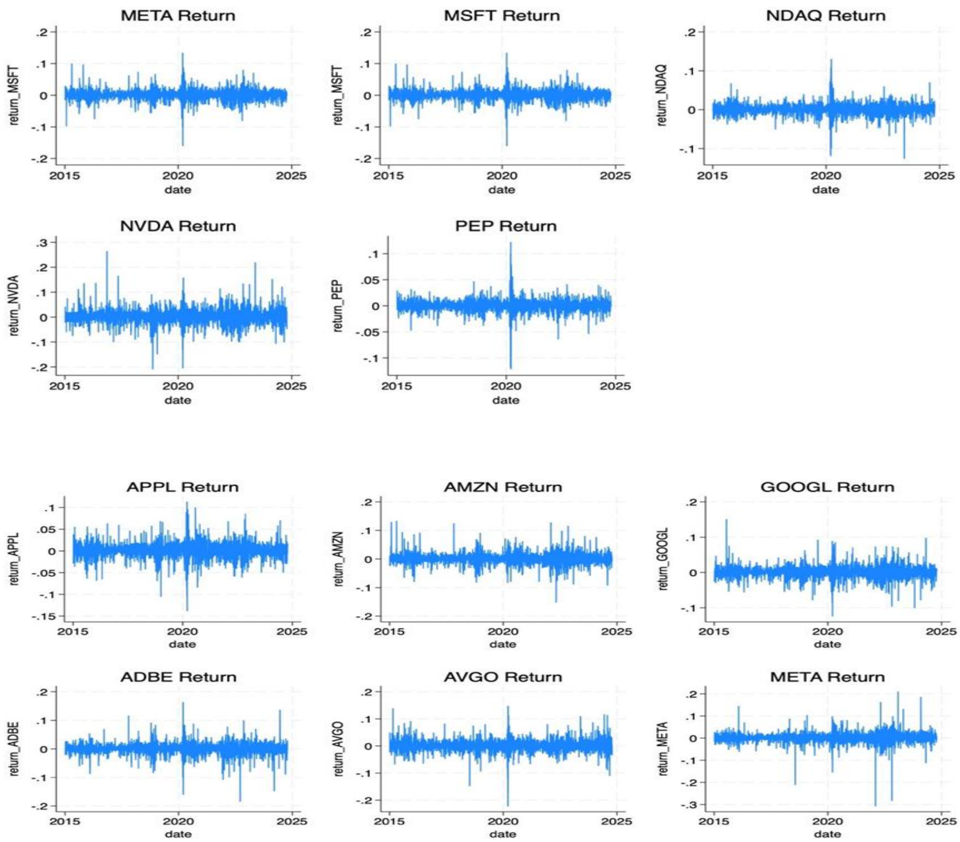
Figure 1. *Daily closing prices of eleven U.S. companies from January 2015 to October 2024*





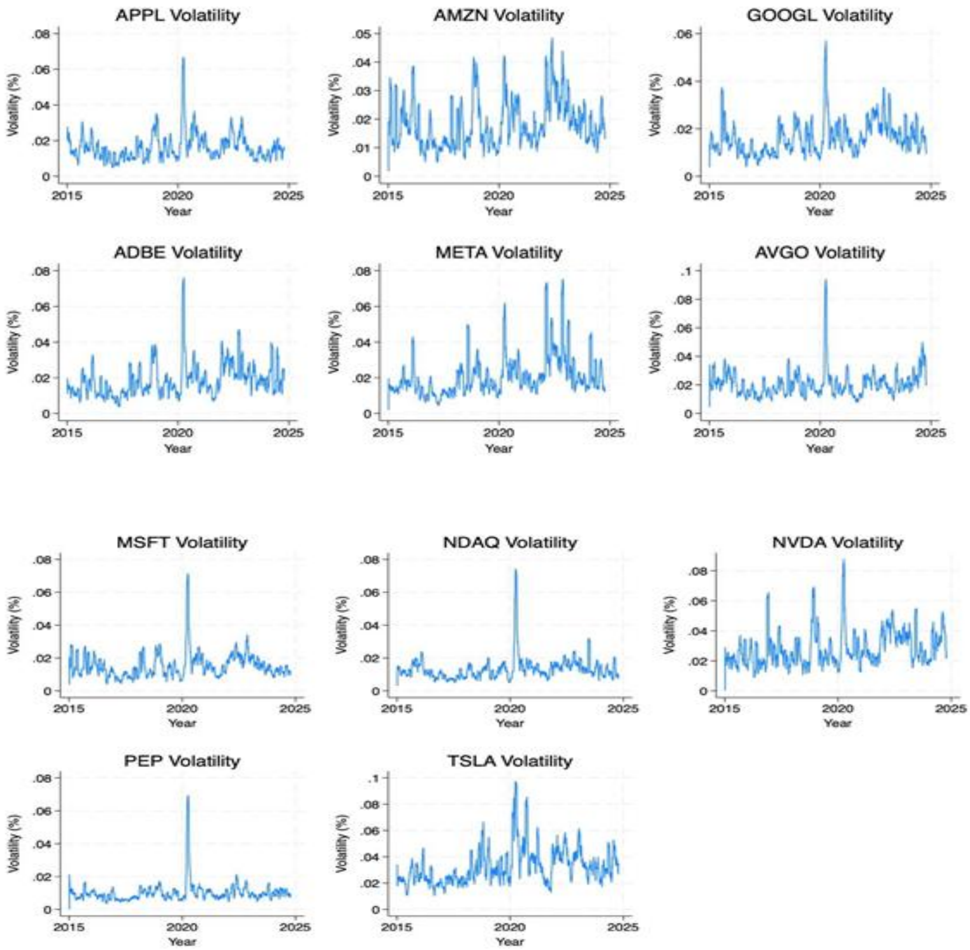
Source: *Stata 18 & Co.*

Figure 2. *Daily log returns of eleven U.S. companies from January 2015 to October 2024*



Notes: *Returns are computed as first differences of logarithmic prices. The plot reveals short-term fluctuations, fat tails, and volatility clustering typical of equity returns.*
Source: *Stata 18 & Co.*

Figure 3. *Thirty-day rolling volatility of eleven U.S. companies from January 2015 to October 2024*



Source: *Stata 18 & Co*

4.1 Descriptive Statistics

Table 1 reports summary statistics for daily returns. The results indicate that mean returns are close to zero, consistent with the characteristics of high-frequency equity data.

Standard deviations vary across firms, with NVDA and TSLA exhibiting the highest return volatility, while PEP displays the lowest. Minimum and maximum values confirm the presence of extreme observations, reflecting market turbulence during crisis episodes.

Table 1. *Descriptive statistics for returns*

Variable	Obs	Mean	Std. Dev.	Min	Max
return AAPL	2462	.0009	.0181	-.1377	.1131
return AMZN	2462	.001	.0206	-.1514	.1324
return GOOGL	2462	.0007	.0179	-.1236	.1506
return ADBE	2462	.0008	.0209	-.1838	.1631
return META	2462	.0008	.024	-.3064	.2093
return AVGO	2462	.0012	.0229	-.2219	.1471
return MSFT	2462	.0009	.0172	-.1595	.1329
return NDAQ	2462	.0006	.0151	-.1257	.1299
return NVDA	2462	.0023	.0307	-.2079	.2637
return PEP	2462	.0003	.0118	-.1214	.1217
return TSLA	2462	.0011	.0356	-.2365	.1815

Source: *Author's calculations.*

Table 2 presents descriptive statistics for the thirty-day rolling volatility series. The results show that volatility is heterogeneous across firms. Technology firms such as NVDA and TSLA demonstrate higher mean volatility and wider ranges, while consumer staples such as PEP exhibit lower and more stable volatility patterns. These observations are consistent with sectoral risk differences and confirm the suitability of the sample for spillover analysis.

Table 2. *Descriptive statistics for volatility*

Variable	Obs	Mean	Std. Dev.	Min	Max
AAPL volatility	2461	.0164	.0076	.0049	.0668
AMZN volatility	2461	.0188	.0085	.0018	.0485
GOOGL volatility	2461	.0164	.0072	.0039	.057
ADBE volatility	2461	.0186	.0094	.0038	.0761
META volatility	2461	.021	.0117	.0019	.0753
AVGO volatility	2461	.021	.0095	.0046	.094
MSFT volatility	2461	.0155	.0077	.0039	.0712
NDAQ volatility	2461	.0133	.0071	.0031	.0742
NVDA volatility	2461	.0282	.0118	.0003	.0875
PEP volatility	2461	.0101	.0062	0	.0693
TSLA volatility	2461	.0327	.0136	.0105	.0971

Source: *Author's calculations.*

4.2 Granger Causality Tests

Table 3a and Appendix Tables **A.1–A.10** report pairwise Granger-causality results for volatility (Wald χ^2, df=2). Several statistically significant predictive linkages emerge. For AAPL as the dependent series, MSFT, NDAQ, and PEP significantly Granger-cause AAPL volatility (p = 0.013, 0.014, and 0.004). META appears as a transmitter toward AMZN, GOOGL, and ADBE, while cross-sector effects are evident with PEP predicting the volatilities of MSFT, AVGO, and NVDA.

Overall, the results reveal a network of firm-to-firm spillovers concentrated in technology, with notable links to consumer and financial firms. Using $p<0.10$ as a screening threshold and emphasizing $p\leq 0.05$ for interpretation, we find a technology-centered spillover network with several cross-sector bridges (see Table 4a). Links with $p\in(0.05, 0.10)$ are viewed as suggestive and hypothesis-generating.

Note: The null hypothesis is that past volatility of the predictor does not help predict the dependent firm's volatility beyond the dependent's own lags. Values with $p < 0.10$ are treated as significant (direction is row → column).

Tables 3a (exemplar) and A1–A10 (Appendix) report pairwise Granger-causality results for volatility (Wald χ^2, df=2). Several statistically significant predictive linkages emerge at $p<0.10$. For AAPL as the dependent series, MSFT, NDAQ, and PEP significantly Granger-cause AAPL volatility ($p=0.013$, 0.014, and 0.004). Within technology, we find dense bidirectional clusters; cross-sector links are present as well—most notably PEP → MSFT/AVGO/NVDA.

Table 3a. *Granger causality for AAPL volatility (dependent: AAPL; df = 2)*

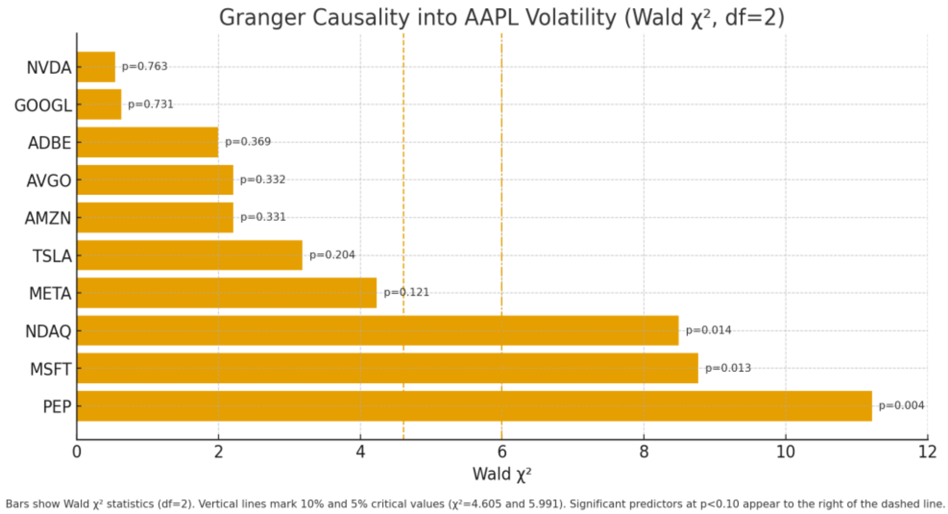
Predictor (row → AAPL)	χ^2	P	Sig.
PEP volatility	11.213	0.004	Yes
MSFT volatility	8.762	0.013	Yes
NDAQ volatility	8.487	0.014	Yes
META volatility	4.23	0.121	
TSLA volatility	3.184	0.204	
AMZN volatility	2.21	0.331	
AVGO volatility	2.206	0.332	
ADBE volatility	1.992	0.369	
GOOGL volatility	0.627	0.731	
NVDA volatility	0.54	0.763	

Note: *Lag length fixed at L=2 for comparability. Full per-firm results appear in Appendix A, Tables A1–A10. Reported p-values are unadjusted.*
Source: *Author's calculations.*

Taken together, the results from Table 3a and Appendix Tables A.1–A.10 indicate notable volatility interdependencies across the eleven companies. Several robust linkages appear within the technology sector: for example, ADBE is significantly influenced by META, AVGO, and NVDA, while META itself is affected by GOOGL, ADBE, MSFT, and PEP. Microsoft's volatility shows strong connections to NDAQ and PEP, and NVDA is significantly driven by PEP.

Cross-sector interactions are also evident: PEP volatility is significantly influenced by AMZN, META, AVGO, MSFT, and NVDA, while AAPL volatility is shaped by both technology peers (MSFT, NDAQ) and the consumer staple PEP. Tesla's volatility is linked to META and NVDA, underscoring the influence of major technology firms on growth-sensitive stocks.

Figure 4. *Granger Causality into NVDA Volatility (Wald χ², df=2; higher bars = stronger evidence*



Source: *Own elaboration.*

Overall, these findings suggest that while many firms exhibit independent volatility dynamics, certain companies—particularly META, MSFT, PEP, and NVDA—serve as important transmitters of shocks. AAPL volatility, for instance, is largely independent of most firms, yet shows meaningful linkages with MSFT, NDAQ, and PEP, highlighting the presence of both intra-technology spillovers and cross-sector connections with consumer staples.

This highlights the presence of both intra-technology spillovers and meaningful cross-sectoral linkages, with practical implications for risk management, diversification, and monitoring systemic vulnerabilities.

4.3 Spillover Matrices

Tables 4a–4b summarize the statistically significant spillover directions in matrix form. The matrices highlight the presence of concentrated transmission around key technology firms such as META, MSFT, and NVDA, while also capturing notable cross-sector connections, most prominently between technology firms and the consumer staple PEP. The results confirm that certain companies function as central nodes in the volatility network, transmitting shocks across multiple firms and sectors.

The evidence suggests that volatility in U.S. mega-cap companies cannot be analyzed in isolation. Instead, firm-to-firm interdependencies must be considered, particularly those emanating from technology leaders, as they reduce the effectiveness of traditional sector-based diversification strategies and create potential channels for systemic risk propagation.

Table 4a. *Spillover Matrix Among Individual Stocks*

	AAPL	AMZN	GOOGL	ADBE	META	AVGO	MSFT	NDAQ	NVDA	PEP	TSLA
AAPL		0.331	0.731	0.369	0.121	0.332	0.013	0.014	0.763	0.004	0.204
AMZN	0.512		0.115	0.451	0.000	0.883	0.165	0.503	0.972	0.096	0.580
GOOGL	0.872	0.355		0.024	0.383	0.223	0.764	0.399	0.881	0.126	0.013
ADBE	0.399	0.413	0.676		<0.001	0.003	0.946	0.415	0.021	0.003	0.227
META	0.255	0.169	<0.001	0.032		0.349	0.004	0.713	0.083	0.031	0.181
AVGO	0.245	0.595	0.750	0.493	0.708		0.107	0.009	0.053	<0.001	0.875
MSFT	0.528	0.239	0.851	0.391	0.765	0.690		0.004	0.161	<0.001	0.248
NDAQ	0.402	0.209	0.823	0.330	0.190	0.033	0.005		0.170	0.065	0.415
NVDA	0.545	0.288	0.706	0.556	0.332	0.143	0.832	0.740		<0.001	0.878
PEP	0.538	0.009	0.139	0.391	0.025	0.009	0.002	0.085	0.034		0.051
TSLA	0.067	0.189	0.749	0.206	0.001	0.255	0.990	0.240	0.050	0.729	

Notes: *Cells report p-values for Granger causality in volatility (row → column). Entries with $p < 0.10$ indicate significant spillovers. Diagonal entries are omitted. Given the number of pairwise tests, some rejections at $p<0.10$ may occur by chance. We therefore highlight $p \leq 0.05$ links in bold and treat $p \in (0.05, 0.10)$ as suggestive.*
Source: *Author's calculations.*

Table 4b. *Spillover Matrix Among Individual Stocks*

	AAPL	AMZN	GOOGL	ADBE	META	AVGO	MSFT	NDAQ	NVDA	PEP	TSLA
AAPL		0.881	0.003	0.969	0.039	0.059	<0.001	0.018	0.575	0.157	0.028
AMZN	0.414		0.291	0.474	<0.001	0.530	0.021	0.730	0.871	0.350	0.388
GOOGL	0.461	0.870		0.438	0.461	0.194	0.083	0.211	0.569	0.265	0.385
ADBE	0.046	0.192	0.680		0.028	0.187	0.162	0.211	0.010	0.003	0.080
META	0.060	0.148	<0.001	0.138		0.251	0.288	0.882	0.148	0.295	0.171
AVGO	0.013	0.135	0.631	0.973	0.552		0.003	0.035	0.377	<0.001	0.387
MSFT	0.428	0.378	0.494	0.987	0.139	0.163		0.099	0.774	0.003	0.197
NDAQ	0.865	0.298	0.688	0.793	0.709	0.001	0.001		0.353	0.231	0.864
NVDA	0.600	0.599	0.600	0.558	0.029	0.147	0.072	0.003		0.087	0.591
PEP	0.273	0.633	0.037	0.344	0.299	<0.001	0.036	0.021	0.159		0.700
TSLA	0.834	0.582	0.438	0.121	0.618	0.531	0.041	0.079	0.134	0.200	

Source: *Author's calculations.*

4.3.1 Interpretation of Tables 4a–4b

Using p<0.10 as the significance cut-off, the matrix paints a clear picture of a technology-centered network with a few powerful cross-sector bridges. Within tech, META, ADBE, AVGO, and MSFT are not isolated movers: META's volatility helps forecast several peers—GOOGL, ADBE, MSFT, and even NVDA—signaling that shocks around social-media/advertising and AI compute spill rapidly across adjacent platforms and chips. ADBE also behaves like a hub, transmitting to META, AVGO, NVDA, and the consumer staple PEP; this is consistent with software-suite exposures that cut across both enterprise IT and supply chains.

AVGO and MSFT add to the internal tech circulation (e.g., to NDAQ and PEP), while NDAQ, though a market-infrastructure firm, sends signals back into the tech complex (to AVGO and MSFT), suggesting a feedback loop between trading conditions and large-cap tech volatility.

The most striking cross-sector conduit is PEP. Despite its staple profile, PEP's volatility anticipates moves in multiple tech names (AMZN, META, AVGO, MSFT, NVDA) as well as NDAQ and TSLA. Interpreted economically, this points to a broad "macro/flows" channel: when defensive or cash-flow-stable names start to tremble, the tremor often reaches growth assets soon after.

On the receiving side, AAPL's volatility responds to MSFT, NDAQ, and PEP, underlining that even the largest single name is not insulated from tech-peer dynamics and market-wide conditions. TSLA, meanwhile, is especially sensitive to technology-driven shocks (notably from GOOGL and META), consistent with its growth-dependent risk profile.

Equally informative are the absences: proposed narratives that GOOGL or AMZN transmit directly to NVDA are not supported at conventional levels here. Instead, NVDA's notable incoming links arise via PEP and (more weakly) other tech senders, hinting that chipmaker volatility may be more exposed to broad demand/positioning pulses than to any single platform firm. Overall, the matrix depicts a dense tech core, a surprisingly influential consumer-staple bridge, and two-way ties with market infrastructure—exactly the kind of configuration that can undermine naïve sector diversification and amplify system-wide swings when a few central nodes are hit.

Table 4b extends the network with several additional transmitters. AAPL sends volatility to GOOGL (p=0.003), META (p=0.039), MSFT (p<0.001), and TSLA (p=0.028), underscoring its central role. AMZN influences META (p<0.001), while GOOGL affects PEP (p=0.037). Software exposures are broad: ADBE → META (p=0.028), NVDA (p=0.010), and PEP (p=0.003). Hardware–platform ties appear via AVGO → MSFT (p=0.003), and market infrastructure feeds back into tech with NDAQ → AVGO and NDAQ → MSFT (both p=0.001). We also observe NVDA → NDAQ (p=0.003). On the cross-sector side, PEP again emerges as a bridge, transmitting to AVGO ($p<0.001$). Overall, Table 4b reinforces a tech-centered core with meaningful links to consumer staples and market infrastructure.

Taken together, the evidence highlights the presence of both intra-technology spillovers and important cross-sector linkages. META, MSFT, NVDA, and PEP emerge as central transmitters of volatility, underscoring their systemic relevance within the network of U.S. mega-cap firms. These findings reinforce the importance of accounting for firm-level interdependencies when designing portfolio diversification strategies and monitoring systemic vulnerabilities in equity markets.

5. Discussion

The results of the empirical analysis indicate that volatility shocks are not confined to individual firms but propagate across the network of leading U.S. companies. The concentration of significant spillovers within the technology sector confirms the systemic role of firms such as META, MSFT, and NVDA. At the same time, the presence of cross-sector linkages, particularly those involving PEP and NDAQ, demonstrates that volatility transmission extends beyond sectoral boundaries and affects consumer staples and financial services.

These findings have several implications. From the perspective of portfolio construction, reliance on sector-based diversification strategies may deliver less risk reduction than anticipated. Investors exposed to technology stocks may still be indirectly affected by shocks transmitted to consumer and financial firms. In addition, risk managers should incorporate firm-to-firm and cross-sector conditional dynamics into stress testing and hedging strategies, recognizing that key transmitters can amplify volatility across the market.

The results also contribute to the broader literature on volatility transmission. Previous studies emphasized spillovers across countries, indices, or sectors (Kumar, 2013; Gamba-Santamaria *et al.,* 2019; Xu *et al.,* 2019).

The present evidence adds a firm-level dimension, highlighting the role of individual companies in shaping systemic vulnerabilities. By identifying specific transmitters, the analysis advances understanding of how volatility shocks originate and spread within U.S. equity markets.

6. Limitations

Several limitations of the present study should be acknowledged. First, the use of pairwise Granger causality tests restricts the analysis to bilateral relationships and does not fully account for higher-order interactions or the role of common factors influencing multiple firms simultaneously. Second, volatility is proxied by the thirty-day rolling standard deviation of returns, which, while widely used, may not capture latent volatility states.

Alternative approaches such as multivariate GARCH specifications, realized volatility measures, or stochastic volatility models could provide additional depth. Third, the sample period spans both pre-crisis and post-crisis subperiods. Although this allows for a broad perspective, it may obscure structural changes in volatility dynamics. Formal structural-break analysis could refine inference by distinguishing between regime-dependent spillover patterns.

The analysis entails numerous pairwise Granger tests, increasing the likelihood of false positives. We report unadjusted p-values and frame the findings as exploratory. Future work should implement false-discovery-rate or familywise-error controls (e.g., Benjamini–Hochberg or Bonferroni) and reassess which links remain significant under multiplicity correction.

7. Conclusion

The study provides empirical evidence of statistically significant volatility spillovers among eleven major U.S. firms during the period 2015–2024. The results demonstrate that spillovers are concentrated within the technology sector, with META, MSFT, and NVDA identified as key transmitters of volatility, and that cross-sector linkages extend these effects to consumer and financial firms such as PEP and NDAQ. These findings highlight the importance of monitoring firm-level interdependencies when designing portfolio diversification strategies and conducting systemic risk assessments.

The analysis contributes to the literature by shifting the focus from aggregate indices and sectors to firm-level dynamics within the U.S. mega-cap universe. This perspective enhances the understanding of how shocks propagate across firms and provides practical insights for investors, risk managers, and policymakers.

Future research should extend the scope beyond U.S. firms to incorporate cross-country comparisons, particularly in emerging markets where institutional structures may generate different transmission mechanisms. Methodologically, the application of multivariate GARCH frameworks, network-based approaches, and structural-break techniques could provide a more comprehensive assessment of volatility dynamics. Such extensions would deepen both academic inquiry and practical oversight of systemic vulnerabilities in financial markets.

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Appendix:

This study reports unadjusted p-values due to its exploratory scope. A formal false-discovery-rate adjustment (Benjamini–Hochberg at q=0.10) and Bonferroni-type familywise controls are left for future extensions and will be provided upon request.

Table A1. *Granger causality Wald test results for AMZN volatility (dependent variable: AMZN)*

Hypothesis	Predictor variable	χ^2	df	p-value
AMZN_volatility	AAPL volatility	1.338	2	0.512
	GOOGL volatility	4.326	2	0.115
	ADBE volatility	1.592	2	0.451
	META volatility	104.410	2	<0.001
	AVGO volatility	0.249	2	0.883
	MSFT volatility	3.609	2	0.165
	NDAQ volatility	1.374	2	0.503
	NVDA volatility	0.057	2	0.972
	PEP volatility	4.695	2	0.096
	TSLA volatility	1.089	2	0.580

Source: *Author's calculations.*

Table A2. *Granger causality Wald test results for GOOGL volatility (dependent variable: GOOGL)*

Hypothesis	Predictor variable	χ^2	df	p-value
GOOGL_volatility	AAPL volatility	0.274	2	0.872
	AMZN volatility	2.073	2	0.355
	ADBE volatility	7.474	2	0.024
	META volatility	1.918	2	0.383
	AVGO volatility	3.001	2	0.223
	MSFT volatility	0.538	2	0.764
	NDAQ volatility	1.839	2	0.399
	NVDA volatility	0.254	2	0.881
	PEP volatility	4.135	2	0.126
	TSLA volatility	8.690	2	0.013

Source: *Author's calculations.*

Table A3. *Granger causality Wald test results for ADBE volatility (dependent variable: ADBE)*

Hypothesis	**Predictor variable**	**χ^2**	**df**	**p-value**
ADBE_volatility	AAPL volatility	1.838	2	0.399
	AMZN volatility	1.770	2	0.413
	GOOGL volatility	0.783	2	0.676
	META volatility	16.629	2	<0.001
	AVGO volatility	11.647	2	0.003
	MSFT volatility	0.110	2	0.946
	NDAQ volatility	1.761	2	0.415
	NVDA volatility	7.751	2	0.021
	PEP volatility	11.658	2	0.003
	TSLA volatility	2.570	2	0.277

Source: *Author's calculations.*

Table A4. *Granger causality Wald test results for META volatility (dependent variable: META)*

Hypothesis	**Predictor variable**	**χ^2**	**df**	**p-value**
META_volatility	AAPL volatility	2.736	2	0.255
	AMZN volatility	3.554	2	0.169
	GOOGL volatility	31.762	2	<0.001
	ADBE volatility	6.866	2	0.032
	AVGO volatility	2.107	2	0.349
	MSFT volatility	11.174	2	0.004
	NDAQ volatility	0.678	2	0.713
	NVDA volatility	4.978	2	0.083
	PEP volatility	6.961	2	0.031
	TSLA volatility	3.419	2	0.181

Source: *Author's calculations.*

Table A5. *Granger causality Wald test results for AVGO volatility (dependent variable: AVGO)*

Hypothesis	**Predictor variable**	**χ^2**	**df**	**p-value**
AVGO_volatility	AAPL volatility	2.812	2	0.245
	AMZN volatility	1.039	2	0.595
	GOOGL volatility	0.576	2	0.750
	ADBE volatility	1.413	2	0.493
	META volatility	0.692	2	0.708
	MSFT volatility	4.477	2	0.107
	NDAQ volatility	9.331	2	0.009
	NVDA volatility	5.891	2	0.053
	PEP volatility	22.749	2	<0.001
	TSLA volatility	0.267	2	0.875

Source: *Author's calculations.*

Table A6. *Granger causality Wald test results for MSFT volatility (dependent variable: MSFT)*

Hypothesis	**Predictor variable**	**χ^2**	**df**	**p-value**
MSFT_volatility	AAPL volatility	1.277	2	0.528
	AMZN volatility	2.861	2	0.239
	GOOGL volatility	0.322	2	0.851
	ADBE volatility	1.877	2	0.391
	META volatility	0.535	2	0.765
	AVGO volatility	0.743	2	0.690
	NDAQ volatility	10.843	2	0.004
	NVDA volatility	3.656	2	0.161
	PEP volatility	31.123	2	<0.001
	TSLA volatility	2.790	2	0.248

Source: *Author's calculations.*

Table A7. *Granger causality Wald test results for NDAQ volatility (dependent variable: NDAQ)*

Hypothesis	**Predictor variable**	**χ^2**	**df**	**p-value**
NDAQ_volatility	AAPL volatility	1.821	2	0.402
	AMZN volatility	3.134	2	0.209
	GOOGL volatility	0.389	2	0.823
	ADBE volatility	2.216	2	0.330
	META volatility	3.325	2	0.190
	AVGO volatility	6.797	2	0.033
	MSFT volatility	10.648	2	0.005
	NVDA volatility	3.545	2	0.170
	PEP volatility	5.464	2	0.065
	TSLA volatility	1.757	2	0.415

Source: *Author's calculations.*

Table A8. *Granger causality Wald test results for NVDA volatility (dependent variable: NVDA)*

Hypothesis	**Predictor variable**	**χ^2**	**df**	**p-value**
NVDA_volatility	AAPL volatility	1.213	2	0.545
	AMZN volatility	2.486	2	0.288
	GOOGL volatility	0.695	2	0.706
	ADBE volatility	1.176	2	0.556
	META volatility	2.208	2	0.332
	AVGO volatility	3.896	2	0.143
	MSFT volatility	0.370	2	0.831
	NDAQ volatility	0.601	2	0.740
	PEP volatility	31.475	2	<0.001
	TSLA volatility	0.261	2	0.878

Source: *Author's calculations.*

Table A9. *Granger causality Wald test results for PEP volatility (dependent variable: PEP)*

Hypothesis	Predictor variable	χ^2	df	p-value
PEP_volatility	AAPL volatility	1.239	2	0.538
	AMZN volatility	9.352	2	0.009
	GOOGL volatility	3.950	2	0.139
	ADBE volatility	1.880	2	0.391
	META volatility	7.349	2	0.025
	AVGO volatility	9.399	2	0.009
	MSFT volatility	12.341	2	0.002
	NDAQ volatility	4.921	2	0.085
	NVDA volatility	6.765	2	0.034
	TSLA volatility	5.958	2	0.051

Source: *Author's calculations.*

Table A10. *Granger causality Wald test results for TSLA volatility (dependent variable: TSLA)*

Hypothesis	Predictor variable	χ^2	df	p-value
TSLA_volatility	AAPL volatility	5.417	2	0.067
	AMZN volatility	3.328	2	0.189
	GOOGL volatility	0.578	2	0.749
	ADBE volatility	3.165	2	0.206
	META volatility	13.092	2	0.001
	AVGO volatility	2.731	2	0.255
	MSFT volatility	0.021	2	0.990
	NDAQ volatility	2.857	2	0.240
	NVDA volatility	5.982	2	0.050
	PEP volatility	0.632	2	0.729

Source: *Author's calculations.*