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Dynamic Volatility Spillovers Between Global Volatility Indices and the Magnificent Seven: What Drives System-Wide Volatility Connectedness?

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Abstract

This study examines the dynamic connectedness between the daily volatility series of global volatility indices (VIX, OVX, and GVZ) and those of the Magnificent Seven companies using data from 22 May 2012 to 25 June 2026. The analysis employs the time-varying parameter vector autoregressive (TVP-VAR) connectedness framework to decompose volatility transmission into within-group and cross-group spillovers. Unlike conventional connectedness analyses that focus primarily on aggregate connectedness measures, this decomposition identifies the dominant source of system-wide volatility connectedness. The results reveal a moderate but highly dynamic transmission structure that intensifies during periods of heightened market stress, particularly during the COVID-19 pandemic. The decomposition further reveals that, although the system incorporates equity-, oil-, and gold-market uncertainty through the VIX, OVX, and GVZ, cross-group spillovers between the global volatility indices and the Magnificent Seven remain comparatively limited. Instead, system-wide connectedness is driven primarily by within-group interactions among the Magnificent Seven. Apple, Meta, and Amazon emerge as net volatility transmitters, whereas Microsoft, Alphabet, and NVIDIA act as net receivers. Pairwise spillovers strengthen during major stress episodes, particularly in the VIX–Apple, VIX–Meta, and Amazon–Meta relationships. The main connectedness patterns remain robust across alternative forecast horizons, lag specifications, rolling-window lengths, and the Diebold –Yilmaz connectedness framework. Overall, the findings highlight the dominant role of within-group spillovers in shaping system-wide connectedness and provide practical insights for portfolio diversification, risk management, and hedging.

Keywords: volatility spillovers; TVP-VAR; global volatility indices; Magnificent Seven; dynamic connectedness

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1. Introduction

Uncertainty is a major driver of asset prices and investor behavior in financial markets. When uncertainty rises, investors reassess risk, and market volatility increases (Antonakakis et al., 2013; L. Liu & Zhang, 2015). This response largely reflects higher risk premiums and discount rates. Higher risk premiums reduce demand for risky assets, leading to lower returns and greater volatility (L. Pástor & Veronesi, 2012; L'. Pástor & Veronesi, 2013; Brogaard & Detzel, 2015). Global financial integration facilitates the rapid transmission of these shocks across markets and asset classes (King & Wadhwani, 1990; Diebold & Yilmaz, 2012). Understanding the direction, magnitude, and evolution of volatility spillovers is therefore important for investors, portfolio managers, and policymakers.

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Option-implied volatility indices are widely used to measure financial uncertainty. The VIX is a key indicator of expected equity market volatility and investor risk perceptions (Whaley, 2009; Bekaert & Hoerova, 2014). Uncertainty, however, does not originate solely in equity markets. The OVX reflects uncertainty in the oil market, while the GVZ captures uncertainty in the gold market (Alqahtani & Chevallier, 2020; Antonakakis et al., 2023; F. Liu et al., 2023). These sources of uncertainty may affect large technology firms through distinct economic channels. Oil-market uncertainty may influence energy costs and inflation expectations, particularly given the growing energy requirements of artificial intelligence, cloud computing, and data-center infrastructure, while uncertainty in precious-metal markets may be relevant through both shifts in global risk appetite and the use of metals in semiconductors and electronic hardware. Examining these indices together provides a broader view of how different sources of market uncertainty interact with technology stocks.

The growing market capitalization of the Magnificent Seven—Apple, Microsoft, Alphabet, Amazon, NVIDIA, Meta, and Tesla—has become a defining feature of global capital markets. These firms operate in strategic fields such as artificial intelligence, cloud computing, semiconductors, digital platforms, and electric vehicles. Their large weights in the S&P 500 and their influence on global markets mean that firm-level volatility shocks may spread through the wider financial system.

Research on volatility transmission expanded considerably with the connectedness framework developed by Diebold and Yilmaz (2012, 2014). Antonakakis et al. (2020) later extended this framework using a time-varying parameter vector autoregressive model. The TVP-VAR approach avoids the need for a rolling window, prevents the loss of observations, and adapts quickly to structural change. These features make it suitable for analyzing dynamic financial connectedness.

Three main gaps remain in the literature. Studies that jointly examine the VIX, OVX, and GVZ within a single system are limited. The dynamic transmission of volatility between these indices and the Magnificent Seven companies has not been sufficiently examined. Existing connectedness studies largely focus on total and directional connectedness measures, leaving limited evidence on whether system-wide connectedness is driven by interactions within economically distinct groups or by volatility transmission between them. This distinction is important because a high level of total connectedness does not necessarily indicate strong cross-market transmission between global volatility indices and the Magnificent Seven.

This study examines the dynamic connectedness between changes in the VIX, OVX, and GVZ and the stock volatilities of the Magnificent Seven. The analysis uses daily data from 22 May 2012 to 25 June 2026. It applies the TVP-VAR connectedness approach of Antonakakis et al. (2020). The analysis reports the Total Connectedness Index (TCI), directional connectedness to others (TO), directional connectedness from others (FROM), net total directional connectedness (NET), and net pairwise directional connectedness (NPDC). In addition, total connectedness is decomposed into within-group and cross-group components to determine the extent to which volatility transmission originates from interactions within the Magnificent Seven, interactions among the volatility indices, or transmission between the two groups.

The study makes five contributions. First, it brings equity, oil, and gold volatility indices together within a common system. Second, it examines each Magnificent Seven company separately rather than treating large technology firms as a homogeneous group. Third, the TVP-VAR model captures changes in the transmission structure without relying on an arbitrarily selected rolling-window length. Fourth, the findings provide new firm-level evidence on the direction and evolution of volatility spillovers between major market uncertainty indicators and the Magnificent Seven. Finally, the study decomposes total connectedness into within-group and cross-group components to identify the main source of system-wide volatility connectedness. This decomposition complements standard total and directional connectedness measures by distinguishing whether the observed connectedness arises from interactions within the Magnificent Seven, interactions among the volatility indices, or cross-market transmission between the two groups. This distinction is economically important because high system-wide connectedness does not necessarily imply strong cross-market transmission between global volatility indices and large technology companies.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents the data and methodology. Section 4 reports the empirical results. Section 5 discusses the findings. Section 6 concludes.

2. Literature Review

The literature is organized into three strands: global volatility indices and financial markets, volatility spillovers and connectedness, and empirical research on the Magnificent Seven companies.

2.1. Global Volatility Indices and Financial Markets

The VIX, OVX, and GVZ are widely recognized as forward-looking indicators of uncertainty in equity, energy, and precious metal markets and are widely used to examine information transmission and systemic risk across asset classes. Their interactions are dynamic, with both the intensity and direction of volatility transmission varying across market conditions, sectors, and countries. A long-run cointegration relationship has been documented between the OVX and VIX, becoming stronger under high-volatility regimes and adjusting primarily through the OVX (Li, 2022). Implied volatility measures also contain more information than the underlying oil, gold, and stock prices during periods of low uncertainty, with the VIX emerging as the strongest indicator of market uncertainty (BenSaïda et al., 2022). Recent evidence also points to feedback from equity markets to implied volatility expectations. Aikins and Kurov (2025) show that stock returns drive changes in expected implied volatility, using E-mini S&P 500 futures and VIX futures as proxies for equity-market returns and implied volatility expectations, respectively. This evidence challenges a purely unidirectional interpretation of the equity–volatility nexus and highlights the potential for feedback from equity-market movements to market-based volatility expectations.

The importance of these indices becomes more evident during episodes of financial stress, when volatility spillovers and market connectedness intensify. Stronger connectedness has been observed under heightened uncertainty (Ozcelebi & Kang, 2024), while spillovers from the VIX and OVX to green bond markets increase substantially during extreme market conditions (Long et al., 2022). The OVX also plays a central role in shaping VIX connectedness across global stock markets during stress periods, whereas the GVZ provides potential hedging benefits (Naeem et al., 2023). A similar strengthening of volatility transmission is observed in Borsa Istanbul, where the effects of the VIX, OVX, and GVZ on the risk appetite of different investor groups became more pronounced following the COVID-19 pandemic (Can-Ergün et al., 2023).

The transmission of volatility further depends on market structure, sectoral composition, and country-specific characteristics. Long-run evidence from the United States shows that implied volatility indices jointly influence sectoral returns, with oil- and exchange rate-related uncertainty containing greater informational content than equity market uncertainty (López et al., 2023). During the Russia–Ukraine war, geopolitical shocks altered these transmission mechanisms by generating asymmetric effects and strengthening the hedging and safe-haven roles of the OVX and VIX (Bossman et al., 2023). Similar patterns are reported in emerging markets, where connectedness between the VIX, OVX, and sector indices increases during crises, the information technology sector primarily absorbs external shocks, and international diversification opportunities become more limited (Khan et al., 2025).

The role of the OVX in volatility transmission is highly regime-dependent, with its position in the connectedness network varying across markets and asset classes. Although the OVX generally behaves as a net receiver of shocks and exhibits strong connectedness with implied volatility measures (Antonakakis et al., 2023), its impact on stock returns and hedging effectiveness depends on conditions in both oil and equity markets (F. Liu et al., 2023). During periods of heightened uncertainty, the OVX strengthens volatility transmission among global energy companies (Xie et al., 2024), while evidence from Gulf markets suggests that it can also act as a persistent net shock transmitter following the removal of oil subsidies (AlGhazali et al., 2025).

The GVZ plays a dynamic role in volatility transmission, serving either as a channel of risk propagation or as a hedging instrument depending on market conditions. Crisis periods strengthen the negative conditional relationship between stock returns and implied volatility measures in Gulf markets (Alqahtani & Chevallier, 2020), whereas evidence from China shows opposite effects of oil and gold volatility on equity returns (Yen-Ku et al., 2022). Gold implied volatility provides effective hedging opportunities for socially responsible investments, while oil volatility offers stronger protection for clean and renewable energy assets (Shahid et al., 2023). Across market conditions and investment horizons, the VIX, OVX, and GVZ exhibit changing transmission roles, generally acting as net shock receivers during downturns, whereas the VIX becomes a major net transmitter in rising markets (Yoon et al., 2026).

The evidence shows that the roles of the VIX, OVX, and GVZ vary across market conditions, asset classes, and investment horizons. Examining them within the same system can therefore reveal interactions among distinct channels of financial uncertainty.

2.2. Volatility Spillovers and the Connectedness Literature

The variance-decomposition-based connectedness framework of Diebold and Yilmaz (2012, 2014) has become one of the most widely used approaches for analysing volatility spillovers across financial markets by measuring system-wide connectedness together with the shocks transmitted, received, and net transmitted by each variable. Its extension to a time-varying parameter vector autoregressive (TVP-VAR) framework enables the transmission mechanism to evolve over time without relying on an arbitrarily selected rolling window or sacrificing observations, allowing a more flexible representation of rapidly changing financial systems (Antonakakis et al., 2020). Consequently, the TVP-VAR connectedness framework has been widely adopted to examine dynamic spillovers across different asset classes and market environments. Existing evidence consistently indicates that connectedness is time-varying rather than constant, with financial crises and episodes of heightened uncertainty strengthening both volatility transmission and system-wide connectedness (Gabauer, 2020).

Higher levels of total connectedness have been documented following the COVID-19 outbreak, accompanied by substantial changes in the net transmitter and receiver roles of financial and commodity markets (Ahmad et al., 2021; Z. Liu et al., 2021; Youssef et al., 2021). Similar dynamics have been reported across equity, commodity, energy, and cryptocurrency markets, where periods of market stress increase connectedness, alter transmitter–receiver roles, and change the propagation of oil price and risk shocks across sectors (Shaik et al., 2024; Arı et al., 2024; Sevillano et al., 2024). Comparable evidence is observed across carbon, renewable energy, foreign exchange, and emerging financial markets, including the BRICS economies and Türkiye, where connectedness rises sharply during crises and spillover patterns vary with market conditions, volatility components, and major global events (Bouteska et al., 2024; Gökgöz et al., 2025; Singh et al., 2025; Gherghina et al., 2026; Kepenek & Ağaslan, 2026). Collectively, these findings demonstrate that the TVP-VAR connectedness framework effectively captures evolving transmission mechanisms and changing shock-transmission roles across a wide range of financial systems. However, the existing literature has concentrated primarily on market- and sector-level connectedness, while evidence on dynamic volatility spillovers at the firm level remains comparatively limited.

The portfolio implications of cross-asset connectedness have also received increasing attention. Alam et al. (2023) show that return and volatility connectedness across REITs, NFTs, cryptocurrencies, oil, gold, and other financial assets intensified during the COVID-19 pandemic and the Russia–Ukraine conflict. Their results further indicate that assets with relatively weaker linkages to the broader system can retain diversification and hedging potential during periods of financial stress. These findings highlight the relevance of cross-asset connectedness for assessing diversification opportunities and portfolio resilience under changing market conditions.

2.3. Empirical Research on the Magnificent Seven and Technology Stocks

The strong interdependence among large technology firms can be understood from both network and technological spillover perspectives. Economic networks can propagate idiosyncratic shocks beyond their point of origin through cascading transmission mechanisms (Acemoglu et al., 2012). Although this mechanism was originally developed in the context of intersectoral input–output linkages, it provides a broader theoretical foundation for understanding how shocks may propagate across interconnected economic agents. Technological interdependence provides an additional transmission channel. R&D activity generates economically significant knowledge spillovers across technologically related firms (Bloom et al., 2013), while the returns of technology-linked firms contain predictive information for the subsequent returns of their peers (Lee et al., 2019). Together, these findings suggest that technological and informational linkages can create channels through which firm-specific developments generate broader repricing across interconnected technology firms.

The growing dominance of large technology firms in global equity markets has increased the systemic importance of firm-level volatility. Despite this importance, empirical evidence on dynamic connectedness among all Magnificent Seven companies remains limited, as most studies focus on broader technology-related markets, including information technology, communication services, e-commerce, FinTech, metaverse, and clean technology indices. Although these studies consistently demonstrate that technology-related assets do not behave as a homogeneous group, sector-level analyses may mask important differences in volatility transmission across individual firms. Existing evidence indicates that transmitter and receiver roles vary across companies and evolve with changing market conditions, even within the same sector (Umar et al., 2025; Aslam, 2026). Amazon, for example, has been identified as the dominant volatility transmitter among major e-commerce companies (Arı et al., 2024), while Bitcoin exhibits a connectedness structure distinct from technology and FinTech indices (Assaf et al., 2024). Connectedness between metaverse stocks and digital assets also strengthens during periods of geopolitical conflict (Aharon et al., 2024), highlighting the influence of external factors such as digital asset markets, global uncertainty, and investor sentiment on technology-related volatility. Similar heterogeneity is observed in the relationship between global volatility indices and technology assets. The effects of the VIX, OVX, and GVZ differ across U.S. sectoral returns, with the VIX emerging as the strongest volatility indicator (BenSaïda et al., 2022). Likewise, the information technology sector has been identified as a net volatility receiver within the global uncertainty system (Khan et al., 2025), while commodity volatility indices provide different hedging benefits for clean technology and renewable energy investments (Shahid et al., 2023). Collectively, these findings suggest that technology firms differ substantially in their volatility dynamics because of variations in business models, revenue structures, and exposure to global risk factors.

Recent firm-level evidence also points to volatility transmission from market-wide uncertainty to the Magnificent Seven. Koycu and Nur (2026), using conditional variance series obtained from GARCH(1,1) models, document significant volatility spillovers from the VIX to several Magnificent Seven stocks. Their findings reinforce the relevance of market-based uncertainty for the volatility dynamics of large technology firms. However, their analysis is confined to the VIX and therefore does not capture uncertainty originating from oil and gold markets within the same system. Evidence on firm-level dynamic connectedness involving the full Magnificent Seven group and multiple global volatility indices therefore remains limited.

2.4. Research Gap

The existing literature offers three broad conclusions. The effects of the VIX, OVX, and GVZ have been examined across stock markets, sector indices, and several asset classes. Volatility transmission generally increases during crises and changes with market conditions. Connectedness studies also show that net transmitter and receiver roles vary over time. Research on technology-related assets reveals strong but heterogeneous volatility spillovers across large technology firms and markets.

However, firm-level evidence on volatility transmission between the VIX, OVX, and GVZ and the Magnificent Seven companies within a common system remains limited. Most studies focus on country or sector indices, specific technology segments, or a single volatility indicator. Consequently, it remains unclear how individual Magnificent Seven companies interact with uncertainty originating from equity, oil, and gold markets and how their roles as net volatility transmitters and receivers, together with their pairwise spillover relationships, evolve over time. More importantly, existing evidence remains limited on whether system-wide connectedness is driven primarily by spillovers within the Magnificent Seven, within the volatility-index group, or by cross-group transmission between the two groups. Clarifying this issue is important for understanding whether volatility propagation is shaped mainly by firm-level interactions within the technology sector or by uncertainty originating from broader financial and commodity markets. Moreover, this relationship has not been sufficiently examined using a framework that allows the transmission structure to evolve over time without relying on an arbitrarily selected rolling-window length. To address these gaps, this study combines the three global volatility indices and the Magnificent Seven companies within a TVP-VAR framework and decomposes total connectedness into within-group and cross-group components, thereby providing new evidence on the primary source of system-wide volatility connectedness.

The analysis is guided by the following research questions:

RQ1. What is the overall level of volatility connectedness, and is system-wide connectedness driven primarily by within-group spillovers or cross-group transmission?

RQ2. How do system-wide and cross-group volatility connectedness evolve over time, particularly during periods of heightened market stress?

RQ3. Which global volatility indices and Magnificent Seven companies act as net volatility transmitters and receivers, and how do these roles evolve over time?

RQ4. How do the direction and magnitude of pairwise volatility spillovers between global volatility indices and the Magnificent Seven companies evolve under different market conditions?

3. Methodology and Materials

This study analyzes volatility spillovers between global volatility indices and the Magnificent Seven using the TVP-VAR connectedness framework of Antonakakis et al. (2020). This framework extends the connectedness approach developed by Diebold and Yilmaz (2012, 2014). The TVP-VAR model tracks changes in volatility transmission throughout the sample period. Its coefficients are allowed to vary over time. This feature captures shifts in connectedness during crises, structural breaks, and regime changes. The model does not require a rolling window. It therefore avoids observation loss and removes sensitivity to a researcher-selected window length. The following subsections describe the TVP-VAR connectedness framework, model estimation, dataset, construction of the volatility series, and selection of the variables.

3.1. TVP-VAR Dynamic Connectedness Approach

The TVP-VAR model is expressed within the state-space representation proposed by Antonakakis et al. (2020), as shown in Equations (1) and (2):

$$y_t = A_t z_{t-1} + \varepsilon_t, \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t, \qquad \xi_t \mid \Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

In Equations (1) and (2), y_t denotes the vector of variables $(m \times 1)$, and z_{t-1} denotes the vector of lagged variables $(mp \times 1)$. A_t represents the time-varying coefficient matrix. ε_t denotes the error term, and Σ_t is its time-varying variance–covariance matrix. $vec(A_t)$ represents the vectorized form of the coefficient matrix. ξ_t denotes the state error that determines changes in the coefficients over time, and Ξ_t is its variance–covariance matrix. z_{t-1} denotes the stacked vector of lagged endogenous variables. Ω_{t-1} represents the information set available up to period $t-1$.

The Generalized Forecast Error Variance Decomposition (GFEVD) is calculated within the TVP-VAR connectedness approach proposed by Antonakakis et al. (2020). GFEVD forms the basis of the connectedness framework developed by Diebold and Yilmaz (2012, 2014). It shows how much of each variable's forecast error variance is explained by its own shocks and by shocks from other variables in the system. The variance shares are normalized so that each row sums to one. The normalized GFEVD values are then used to calculate the TCI, TO, FROM, NET, and NPDC measures through the following equations.

$$\widetilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{3}$$

In Equation (3), $\Psi_{\{ij,t\}(H)}$ denotes the generalized impulse response of variable i to a shock in variable j over the H-step-ahead forecast horizon. The conditions $\sum_{j=1}^{m} \widetilde{\phi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m} \widetilde{\phi}_{ij,t}(H) = m$ are satisfied. The numerator represents the cumulative effect of the relevant shock, while the denominator represents the cumulative effect of all shocks in the system. Unlike the Cholesky decomposition, the GFEVD is invariant to the ordering of variables. The TCI, which measures the overall level of connectedness in the system, is calculated in Equation (4).

$$C_t(H) = \frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{m} \widetilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \widetilde{\phi}_{ij,t}(H)} \times 100 = \frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{m} \widetilde{\phi}_{ij,t}(H)}{m} \times 100 \quad (4)$$

In Equation (4), $C_t(H)$ denotes the TCI at time t. The numerator represents the sum of cross-variable volatility spillovers, while the denominator represents total volatility in the system. The TCI therefore measures the percentage magnitude of total volatility spillovers within the system. Higher TCI values indicate stronger connectedness among the variables. Lower values indicate weaker volatility transmission. The TO measure, which represents the total volatility transmitted by a variable to the other variables in the system, is calculated as shown in Equation (5):

$$C_{i\to j,t}(H) = \frac{\sum_{\substack{j=1,\\ i\neq j}}^{m} \widetilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{m} \widetilde{\phi}_{ji,t}(H)} \times 100 \quad (5)$$

In Equation (5), $C_{i\to j,t}(H)$ represents the total volatility transmitted from variable i to the other variables in the system. A higher TO value indicates that the variable has a stronger role as a volatility transmitter. In contrast, the FROM measure represents the total volatility received by a variable from the other variables in the system. It is calculated as shown in Equation (6):

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{\substack{j=1,\\ i\neq j}}^{m} \widetilde{\phi}_{ij,t}(H)}{\sum_{i=1}^{m} \widetilde{\phi}_{ij,t}(H)} \times 100 \quad (6)$$

In Equation (6), $C_{i\leftarrow j,t}(H)$ represents the total volatility received by variable i from the other variables in the system. A higher FROM value indicates greater exposure to volatility shocks originating from other variables.

$$C_{i,t} = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \quad (7)$$

In Equation (7), $C_{i,t}$ denotes the NET value of variable i. NET is calculated as the difference between TO and FROM. A positive NET value identifies the variable as a net volatility transmitter. A negative value identifies it as a net volatility receiver. Values close to zero indicate that the transmitter and receiver roles of the variable are balanced.

$$NPDC_{ij}(H) = \left(\widetilde{\phi}_{ji,t}(H) - \widetilde{\phi}_{ij,t}(H)\right) \times 100 \quad (8)$$

In Equation (8), $NPDC_{ij}(H)$ represents net pairwise directional connectedness between variables i and j. Positive values indicate that volatility is transmitted mainly from variable i to variable j. Negative values indicate transmission from variable j to variable i. A larger absolute value indicates stronger net volatility transmission between the two variables.

To distinguish within-group spillovers from cross-group transmission, the variables were divided into two groups. The first group consists of the VIX, OVX, and GVZ. The second group consists of the Magnificent Seven stocks. The decomposition was implemented using the InternalConnectedness and ExternalConnectedness functions in the ConnectednessApproach package, following Gabauer and Gupta (2018). The internal procedure sets the cross-group elements of the forecast error variance decomposition matrix to zero. The external procedure sets the within-group elements to zero. The TCI, TO, FROM, NET, and NPDC measures were then recalculated from the decomposed matrices. The baseline measures capture connectedness across the full system. The internal measures isolate volatility transmission within each group, while the external measures capture spillovers between the two groups.

3.2. Model Estimation

The TVP-VAR connectedness analysis was conducted using the ConnectednessApproach package in R package version 1.0.4 (Gabauer, 2025). Before model estimation, the optimal lag length was determined through the VARselect procedure (Pfaff, 2008). The Akaike Information Criterion (AIC), Hannan–Quinn Information Criterion (HQ), Schwarz Criterion (SC), and Final Prediction Error (FPE) were considered. The one-lag model recommended by the SC was selected because it provided a more parsimonious specification (nlag = 1). The forecast horizon for the GFEVD was set to 10 periods (nfore = 10). The model was estimated under the BayesPrior specification with forgetting factors of $\kappa_1 = 0.99$ and $\kappa_2 = 0.99$, following the implementation provided by Gabauer and Gupta (2018). The κ_1 coefficient controls the temporal evolution of the time-varying coefficient matrix. The κ_2 coefficient controls the evolution of the variance–covariance matrix (Antonakakis et al., 2020). Values close to one allow the model parameters to be updated more gradually.

3.3. Data

The study uses daily data covering the period from 22 May 2012 to 25 June 2026. The starting date is determined by Meta Platforms Inc. (formerly Facebook), which went public on 18 May 2012. After constructing the return series, all variables were merged by date using Excel Power Query, and only common trading days with available observations for every variable were retained. This procedure resulted in a balanced sample covering the common observation period. Table 1 presents the variables used in the analysis.

Table 1. Definition of Variables.

Variable	Definition
VIX	CBOE Volatility Index
OVX	CBOE Crude Oil Volatility Index
GVZ	CBOE Gold Volatility Index
AMZN	Amazon Inc. stock prices
AAPL	Apple Inc. stock prices
GOOGL	Alphabet Inc. stock prices
META	Meta Platforms Inc. stock prices
MSFT	Microsoft Corporation stock prices
NVDA	NVIDIA Corporation stock prices
TSLA	Tesla Inc. stock prices

The daily closing values of the VIX, OVX, and GVZ were obtained from the official historical database of CBOE Global Markets. The split-adjusted daily closing prices of the Magnificent Seven stocks were obtained from Investing.com. The resulting balanced dataset contains 3538 daily observations for each variable.

3.4. Construction of Volatility Series

To construct the volatility series used in the analysis, the daily logarithmic returns of all variables were first calculated as $r_{i,t} = 100 \times \ln(P_{i,t}/P_{i,t-1})$, and these returns were then squared to obtain the daily volatility measures $VOL_{i,t} = r_{i,t}^2$. This transformation was applied to the stock prices of the Magnificent Seven companies and the VIX, OVX, and GVZ indices. The squared stock returns represent daily price volatility. The transformation applied to the volatility indices captures the magnitude of daily changes in the VIX, OVX, and GVZ. All variables were therefore processed within the same transformation framework to examine the transmission of daily volatility fluctuations across the system. Gherghina et al. (2026) also calculated logarithmic returns for stock market indices, CDS indicators, the VIX, and the OVX and squared these returns to construct the volatility series.

However, the VIX, OVX, and GVZ are already implied volatility measures derived from option prices. Therefore, the squared logarithmic changes in these indices are not interpreted as new estimates of the realized volatility of the underlying assets, but as measures of the magnitude of daily changes in the implied volatility indices. The purpose of this transformation is to examine daily fluctuations in the volatility indices and daily price volatility in the Magnificent Seven stocks within a common empirical framework. Although this close-to-close measure provides a simple and consistent basis for all variables, it may be sensitive to extreme price movements and does not incorporate intraday price information. Realized volatility, range-based measures such as the Parkinson estimator, and GARCH-based conditional volatility estimates provide alternative measures that may capture different volatility dynamics by using additional intraday, price-range, or model-based information. These alternatives, however, rely on different data requirements and modelling assumptions. Squared logarithmic changes are therefore used in this study as a simple and consistent baseline measure at the daily frequency, and the findings are interpreted with the limitations of this measurement choice in mind.

3.5. Selection of Global Volatility Indices

The main reason for selecting the VIX, OVX, and GVZ together is that each represents a distinct source of uncertainty that may affect the Magnificent Seven through different economic and financial transmission channels.

The VIX is derived from S&P 500 option prices and reflects expected volatility in the US equity market. It is widely regarded as the main "fear gauge" of global stock markets. Because the Magnificent Seven companies are among the largest constituents of the S&P 500 by market capitalization, their stock volatility is closely linked to systematic market risk. The VIX is therefore included as a proxy for general market uncertainty and investor risk perception.

The OVX reflects expected volatility in the crude oil market. Oil price uncertainty may influence production costs, inflation expectations, and discount rates through energy costs. This channel has become increasingly relevant with the expansion of artificial intelligence, cloud computing, and large-scale data centers, all of which require substantial energy consumption. The OVX therefore represents macroeconomic uncertainty originating from the energy market.

The GVZ reflects expected volatility in the gold market. Gold is traditionally regarded as a safe-haven asset and provides information about changes in global risk appetite and flight-to-quality behavior. It is also a strategic input in the production of semiconductors, integrated circuits, and electronic connectors because of its high conductivity and resistance to corrosion. The GVZ therefore captures uncertainty related to both financial risk perception and an important production input for the technology sector.

Including these three volatility indices enables uncertainty originating from equity, energy, and precious metal markets to be evaluated simultaneously, providing a more comprehensive framework for examining volatility transmission to the Magnificent Seven.

3.6. Selection of the Magnificent Seven Stocks

The stock variables consist of the volatility series of Apple, Microsoft, Alphabet, Amazon, NVIDIA, Meta, and Tesla. These companies were selected because of their large market capitalizations, high trading volumes, and substantial weights in the S&P 500. They operate in strategic growth areas, including artificial intelligence, cloud computing, digital platforms, semiconductor technologies, and electric vehicles, and play an important role in global capital markets. As a result, volatility shocks originating from these companies may extend beyond the firm level and spread to broader financial markets.

These characteristics make the Magnificent Seven a systemically important group for examining the transmission of global uncertainty. Including these companies allows both the transmission of volatility from global uncertainty indicators and the spillover dynamics within the group to be analyzed within a common framework.

4. Results

This section reports the empirical findings in line with the research questions. It first presents the descriptive statistics, correlation matrix, and unit root test results. The dynamic connectedness results are then reported, focusing on total and group-specific connectedness, directional transmitter–receiver roles, pairwise spillovers, and robustness analysis. The descriptive statistics are reported in Table 2, while the correlation matrix is presented in Table 3.

Table 2 presents the descriptive statistics for the volatility series used in the analysis. All series exhibit positive and statistically significant skewness together with high and statistically significant excess kurtosis, indicating right-skewed distributions with pronounced fat tails. The particularly large skewness and excess kurtosis values observed for the OVX, META, VIX, and MSFT suggest the presence of extreme observations in the volatility distributions. The Jarque–Bera (JB) test rejects the null hypothesis of normality at the 1% significance level for all series. Furthermore, the weighted Ljung–Box Q(10) statistics indicate significant serial correlation in all volatility series. Overall, these characteristics are consistent with the non-normality, fat tails, and volatility clustering commonly observed in financial volatility series.

Table 3 presents the Pearson correlation coefficients for the volatility series used in the analysis. The coefficients are generally low and predominantly positive, indicating weak contemporaneous linear relationships among the variables. The highest correlation among the technology stocks is observed between GOOGL and MSFT (0.473). This is followed by MSFT–NVDA (0.363) and AMZN–AAPL (0.308). All correlation coefficients remain below 0.50, suggesting that the series have distinct volatility dynamics. This pattern supports the use of the TVP-VAR connectedness approach to examine the direction, magnitude, and time variation of volatility transmission.

Table 2. Descriptive Statistics.

Stat	VIX	OVX	GVZ	AMZN	AAPL	GOOGL	META	MSFT	NVDA	TSLA
Mean	62.12	35.58	27.58	4.09	3.16	3.03	6.24	2.74	8.26	12.82
Variance	34,714.87	33,061.5	5754.98	131.88	85.59	79.82	901.93	77.57	625.35	1072.16
Skew.	13.756 ***	26.39 ***	12.348 ***	8.802 ***	10.953 ***	11.11 ***	19.858 ***	13.531 ***	13.388 ***	7.224 ***
Ex. Kurtosis	322.584 ***	896.555 ***	272.543 ***	109.718 ***	175.05 ***	190.852 ***	499.134 ***	279.401 ***	264.408 ***	73.854 ***
JB	15,451,808.27 ***	118,905,794.56 ***	11,039,947.18 ***	1,820,290.39 ***	4,587,935.66 ***	5,442,365.75 ***	36,959,147.32 ***	11,616,033.34 ***	10,411,784.07 ***	834,834.95 ***
Q(10)	212.913 ***	252.402 ***	462.764 ***	113.014 ***	573.161 ***	147.835 ***	14.613 ***	819.069 ***	133.189 ***	204.763 ***

Notes: For ease of presentation, the original variable labels are retained. However, all variables refer to volatility series constructed from squared daily logarithmic returns rather than raw index values or stock prices. JB denotes the Jarque–Bera normality test, and Q(10) denotes the weighted Ljung–Box statistic for serial correlation in the volatility series. The reported significance levels correspond to the p-values of the associated statistical tests. *** denotes significance at the 1% level.

Table 3. Correlation Matrix.

Correlation	VIX	OVX	GVZ	AMZN	AAPL	GOOGL	META	MSFT	NVDA	TSLA
VIX	1.000000									
OVX	0.151941	1.000000								
GVZ	0.205755	0.100751	1.000000							
AMZN	0.072570	0.007740	0.037926	1.000000						
AAPL	0.083119	0.036337	0.124785	0.308335	1.000000					
GOOGL	0.073377	0.044407	0.061111	0.157163	0.149164	1.000000				
META	0.016097	−0.004693	0.027038	0.225140	0.184484	0.182209	1.000000			
MSFT	0.056626	0.066747	0.076867	0.207634	0.231101	0.473302	0.145642	1.000000		
NVDA	0.018678	0.053302	0.046008	0.092275	0.108162	0.270297	0.036034	0.363183	1.000000	
TSLA	0.018273	0.022125	0.038293	0.131050	0.295452	0.067625	0.078919	0.114947	0.047891	1.000000

4.1. Unit Root Test Results

The stationarity properties of the volatility series were examined using the ADF and ERS unit root tests. The results are presented in Table 4.

Table 4. ADF and Elliott–Rothenberg–Stock (ERS) Unit Root Test Results.

	ADF		ERS Point Optimal Test	
Variable	**ADF Test Statistic**	**5% Critical Value**	**ERS P-Statistic**	**5% Critical Value**
VIX	−28.24782	−2.862160	0.022893	3.260000
OVX	−6.907029	−2.862166	1.097787	3.260000
GVZ	−22.60488	−2.862160	0.032443	3.260000
AMZN	−25.06414	−2.862160	0.029489	3.260000
AAPL	−14.07635	−2.862161	0.103134	3.260000
GOOGL	−21.42959	−2.862161	0.037867	3.260000
META	−58.17235	−2.862160	0.119362	3.260000
MSFT	−12.45188	−2.862162	0.133296	3.260000
NVDA	−24.83326	−2.862160	0.026055	3.260000
TSLA	−27.38532	−2.862160	0.048636	3.260000

Note: The null hypothesis of both tests states that the series contains a unit root. The null hypothesis is rejected when the ADF test statistic or the ERS Point Optimal P-statistic is lower than the corresponding critical value.

Table 4 presents the ADF and ERS Point Optimal unit root test results for the volatility series used in the analysis. An intercept-only specification was used in both tests because the series do not contain a deterministic trend. The maximum lag length was set to 29. The appropriate lag lengths were selected automatically using the Schwarz Information Criterion (SIC). The results of both tests reject the null hypothesis of a unit root for all variables at the 5% significance level. The volatility series of the VIX, OVX, GVZ, and all Magnificent Seven companies are therefore stationary at level, I(0). Thus, the stationarity condition required for the TVP-VAR connectedness analysis is satisfied.

4.2. TVP-VAR Connectedness Results

The TVP-VAR connectedness analysis was conducted using the estimation settings described in Section 3.2. The resulting matrix is presented in Table 5.

Table 5 presents the dynamic connectedness matrix obtained from the TVP-VAR connectedness approach. The diagonal elements represent the shares of each variable's forecast error variance explained by its own shocks, whereas the off-diagonal elements represent volatility spillovers across variables. The FROM column reports spillovers received from the rest of the system, while the TO row reports spillovers transmitted to other variables.

The TCI reported in the lower-right corner is 32.76%, while the corrected TCI is 36.40%, indicating a moderate level of system-wide volatility connectedness. Approximately one-third of the forecast error variance is explained by shocks originating from other variables. Figure 1 further shows that this connectedness is driven primarily by within-group spillovers among the Magnificent Seven rather than by cross-group transmission from the global volatility indices. The NET results identify Apple (32.45), Meta (25.85), and Amazon (6.72) as the main net volatility transmitters, whereas Microsoft (−22.03), NVIDIA (−20.41), Alphabet (−14.05), GVZ (−3.37), Tesla (−2.28), OVX (−1.76), and VIX (−1.11) emerge as net volatility receivers. These findings indicate heterogeneous volatility transmission, with technology companies and global volatility indices performing different roles within the system.

Table 5. Dynamic Connectedness Matrix.

Variable	VIX	OVX	GVZ	AMZN	AAPL	GOOGL	META	MSFT	NVDA	TSLA	FROM
VIX	77.89	7.32	5.67	1.21	2.91	1.58	1.23	0.96	0.70	0.53	22.11
OVX	6.47	77.57	3.34	1.27	2.09	2.36	1.28	1.99	1.85	1.78	22.43
GVZ	5.43	3.78	78.68	1.77	3.19	1.52	2.44	1.03	1.30	0.87	21.32
AMZN	0.96	0.79	1.33	62.17	8.06	3.98	14.00	4.74	1.61	2.35	37.83
AAPL	2.07	1.43	1.56	7.55	67.62	3.43	7.10	3.57	2.21	3.45	32.38
GOOGL	1.91	1.66	1.61	6.93	9.68	53.98	8.66	8.43	3.88	3.27	46.02
META	0.61	0.76	1.16	7.24	7.32	3.47	72.77	2.71	0.70	3.25	27.23
MSFT	1.57	1.53	1.18	10.95	14.66	7.86	9.03	45.35	4.62	3.24	54.65
NVDA	1.35	1.74	1.36	4.51	11.13	4.51	4.85	6.08	60.92	3.55	39.08
TSLA	0.62	1.68	0.76	3.09	5.79	3.26	4.48	3.10	1.80	75.43	24.57
TO	21.00	20.67	17.96	44.54	64.83	31.97	53.08	32.61	18.67	22.29	327.63
NET	−1.11	−1.76	−3.37	6.72	32.45	−14.05	25.85	−22.03	−20.41	−2.28	36.40/32.76

Note: The values 36.40 and 32.76 reported in the bottom-right corner represent the corrected Total Connectedness Index (cTCI) and the baseline Total Connectedness Index (TCI), respectively.

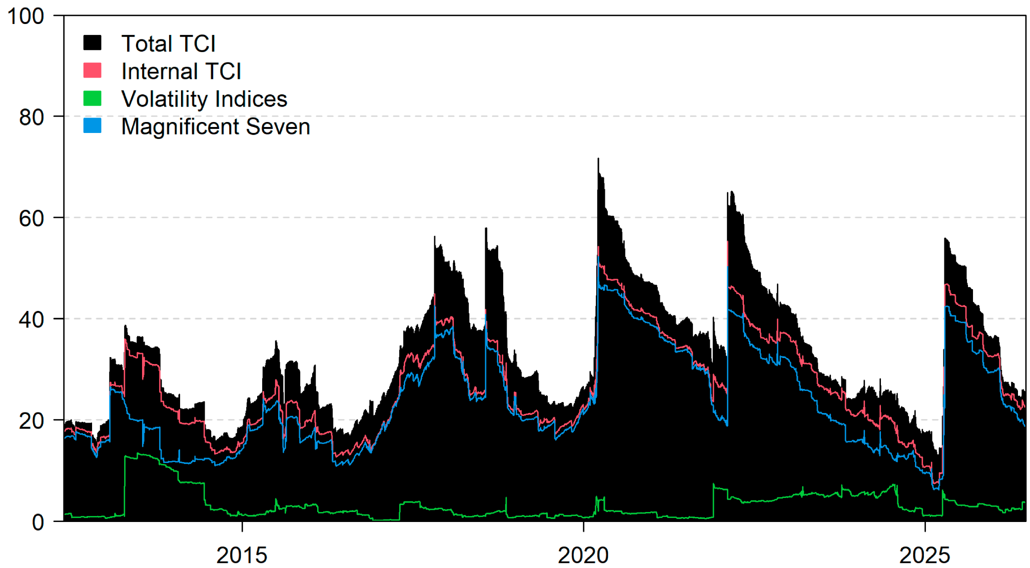

Figure 1. Dynamic Total, Internal, and Group-Specific Connectedness Indices.

Figure 1 presents the dynamic TCI together with the within-group connectedness indices obtained from the TVP-VAR model. The results show that volatility connectedness was highly time-varying and intensified during periods of heightened financial uncertainty. The TCI remained at low to moderate levels during the early years of the sample before rising sharply after 2018 and peaking at approximately 70% during the COVID-19 pandemic in 2020. It subsequently declined and increased again in 2022 amid global inflationary pressures, monetary tightening, and geopolitical risks associated with the Russia–Ukraine war. A further increase in 2025 coincided with heightened trade policy uncertainty following U.S. tariff announcements, changing oil market expectations, and stronger safe-haven demand for precious metals (International Monetary Fund, 2025; World Bank, 2025).

The decomposition results indicate that system-wide connectedness was driven primarily by within-group spillovers among the Magnificent Seven, whereas the contribution of the volatility-index group remained limited. The external TCI (6.15%) and corrected external TCI (6.83%) were substantially lower than the full-system TCI (32.76%). The external NET results indicate modest net volatility transmission from the Magnificent Seven to the global volatility indices. Apple, Meta, and Amazon emerged as the main cross-group transmitters, whereas GVZ and OVX were the main cross-group receivers.

To further examine the time-varying nature of cross-group transmission, Table 6 reports the mean and maximum external TCI across selected market regimes.

Table 6. External Connectedness across Selected Market Regimes.

Period	Mean External TCI (%)	Maximum External TCI (%)	Peak Date
Pre-COVID	5.90	19.19	10 October 2018
COVID-19	7.48	18.02	23 March 2020
Russia–Ukraine and Tightening	11.19	18.96	4 March 2022
AI Expansion	4.27	7.07	9 September 2024
Recent Tariff-Uncertainty Period	5.04	10.01	16 April 2025

Although the average level of external connectedness is relatively low, this value may mask substantial variation in cross-group volatility transmission over time. The dynamic evolution of the external TCI is therefore examined to assess how cross-group connectedness changes under different market conditions. Figure 2 presents the dynamic external connectedness between the global volatility indices and the Magnificent Seven. The dashed vertical lines indicate the COVID-19 pandemic, the onset of the Russia–Ukraine war, the beginning of the Federal Reserve's monetary tightening cycle, and the period of tariff-related uncertainty in 2025.

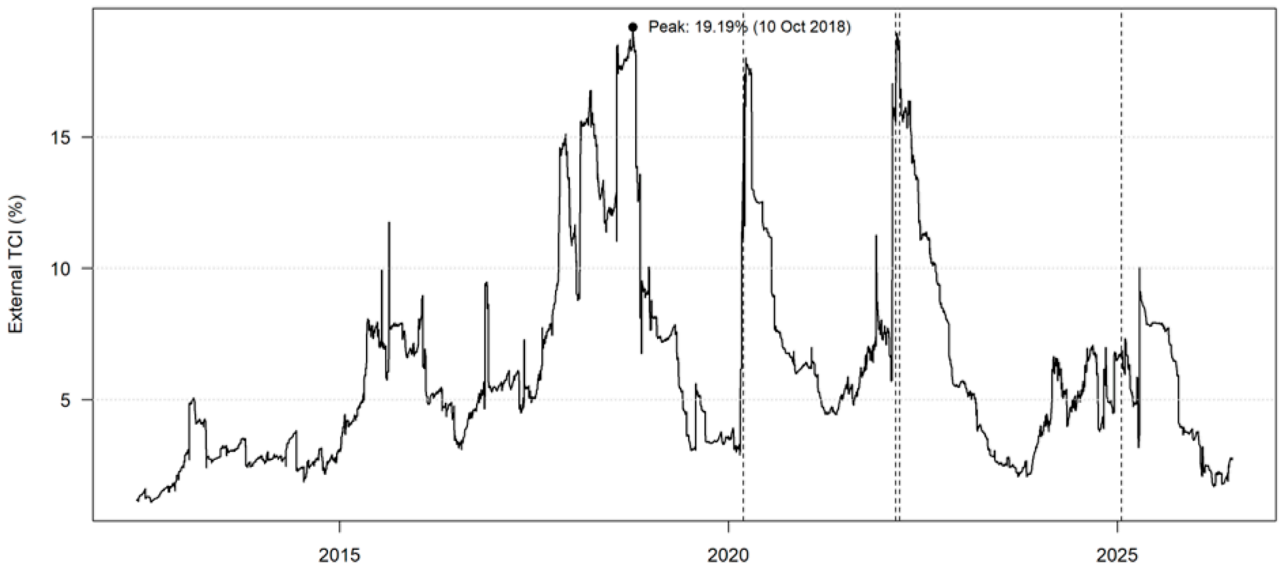

Figure 2. Dynamic Cross-Group Connectedness.

The dynamic external TCI shows substantial variation in cross-group connectedness over the sample period. Although the average external TCI for the full sample is 6.15%, its values range from approximately 1.10% to 19.19%. The highest level of external connectedness is recorded on 10 October 2018, at 19.19%. During the COVID-19 period, external connectedness increases markedly and reaches 18.02% on 23 March 2020. The regime-based results show that cross-group transmission is strongest during the Russia–Ukraine war and monetary tightening period. The average external TCI reaches 11.19%, the highest among the periods examined, with a period-specific maximum of 18.96% on 4 March 2022. This increase coincides with the onset of the Russia–Ukraine war and the Federal Reserve's transition to a monetary tightening cycle. In contrast, the average external TCI declines to 4.27% during the 2023–2024 AI expansion period, indicating considerably lower cross-group connectedness. During the tariff-related uncertainty period in 2025, the average external TCI is 5.04%, although a temporary increase raises it to 10.01% on 16 April 2025. These findings show that the relatively low average level of cross-group connectedness over the full sample can mask pronounced but temporary increases during periods of market stress.

Figure 3 presents the dynamic total and within-group NET connectedness measures obtained from the TVP-VAR model. The black areas represent total NET connectedness, while the red lines represent within-group NET connectedness. Positive values indicate net volatility transmitters, whereas negative values indicate net receivers.

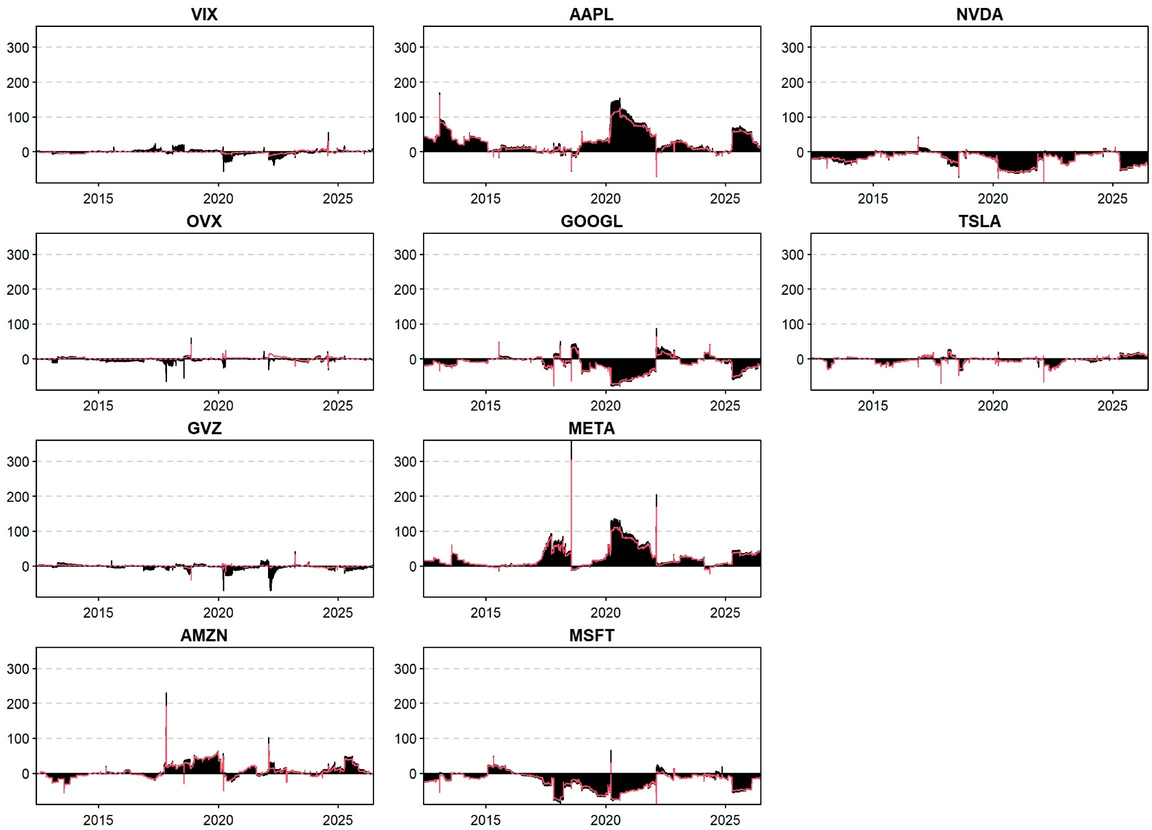

Figure 3. Dynamic Total and Within-Group Net Directional Connectedness. Note: The black shaded areas represent total NET connectedness, while the red lines represent within-group NET connectedness.

META and AAPL remained net transmitters for extended periods, while AMZN became a strong transmitter during certain episodes. In contrast, MSFT, GOOGL, and NVDA generally acted as net receivers. The VIX, OVX, GVZ, and TSLA fluctuated around zero and alternated between transmitter and receiver roles. The close correspondence between the total and within-group NET measures indicates that firm-specific transmission roles were shaped primarily by interactions within the respective groups rather than by cross-group spillovers. The stronger variation observed during periods of heightened financial uncertainty further suggests that these roles were sensitive to changing market conditions. The total and within-group TO and FROM measures reported in Appendix A Figures A1 and A2 support this interpretation, with AAPL, META, and AMZN generally transmitting more volatility to the system and MSFT, GOOGL, and NVDA primarily receiving volatility. This transmission structure became more pronounced during the COVID-19 pandemic and periods of global inflationary pressure. The NPDC analysis in Figures 4–6 further examines how these transmission patterns evolved between each global volatility index and the individual Magnificent Seven stocks.

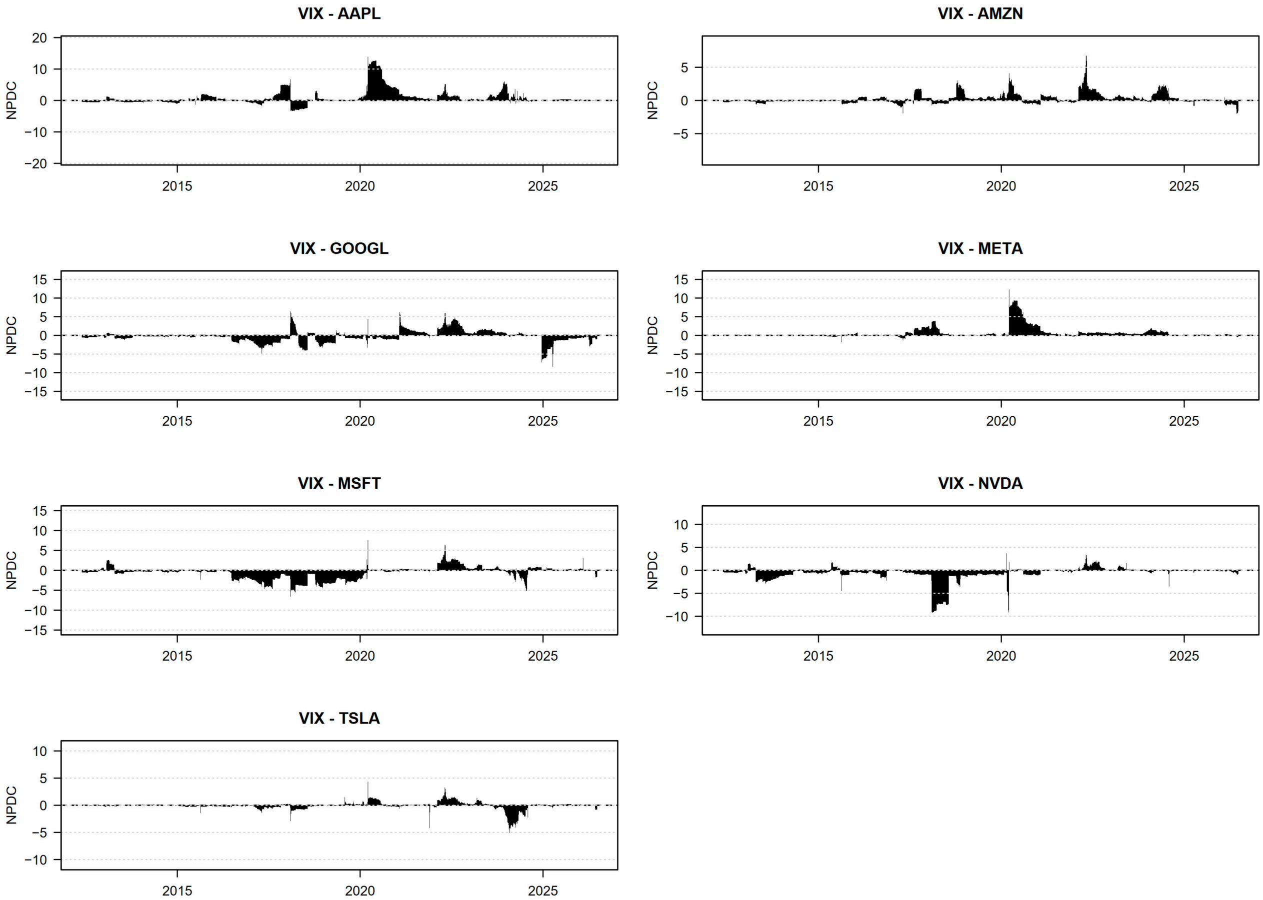

Figure 4. NPDC: VIX to Magnificent Seven Stocks.

Figure 4 presents the dynamic NPDC results between the VIX and the Magnificent Seven stocks. Positive values indicate dominant net volatility transmission from the VIX to the respective stock. Negative values indicate transmission from the stock to the VIX. The results reveal substantial variation in both the direction and magnitude of pairwise transmission over time. During the COVID-19 pandemic, the VIX became a dominant volatility transmitter to AAPL, META, and AMZN, indicating stronger transmission of equity-market uncertainty to these firms during heightened market stress. In contrast, MSFT and NVDA transmitted volatility to the VIX during certain periods, while the direction of transmission for GOOGL and TSLA changed over time. These shifts indicate that the Magnificent Seven did not respond uniformly to market-wide uncertainty and that their relationships with the VIX depended on prevailing market conditions. Overall, the results highlight a dynamic and bidirectional transmission structure rather than a stable one-way flow of volatility from the VIX to technology stocks.

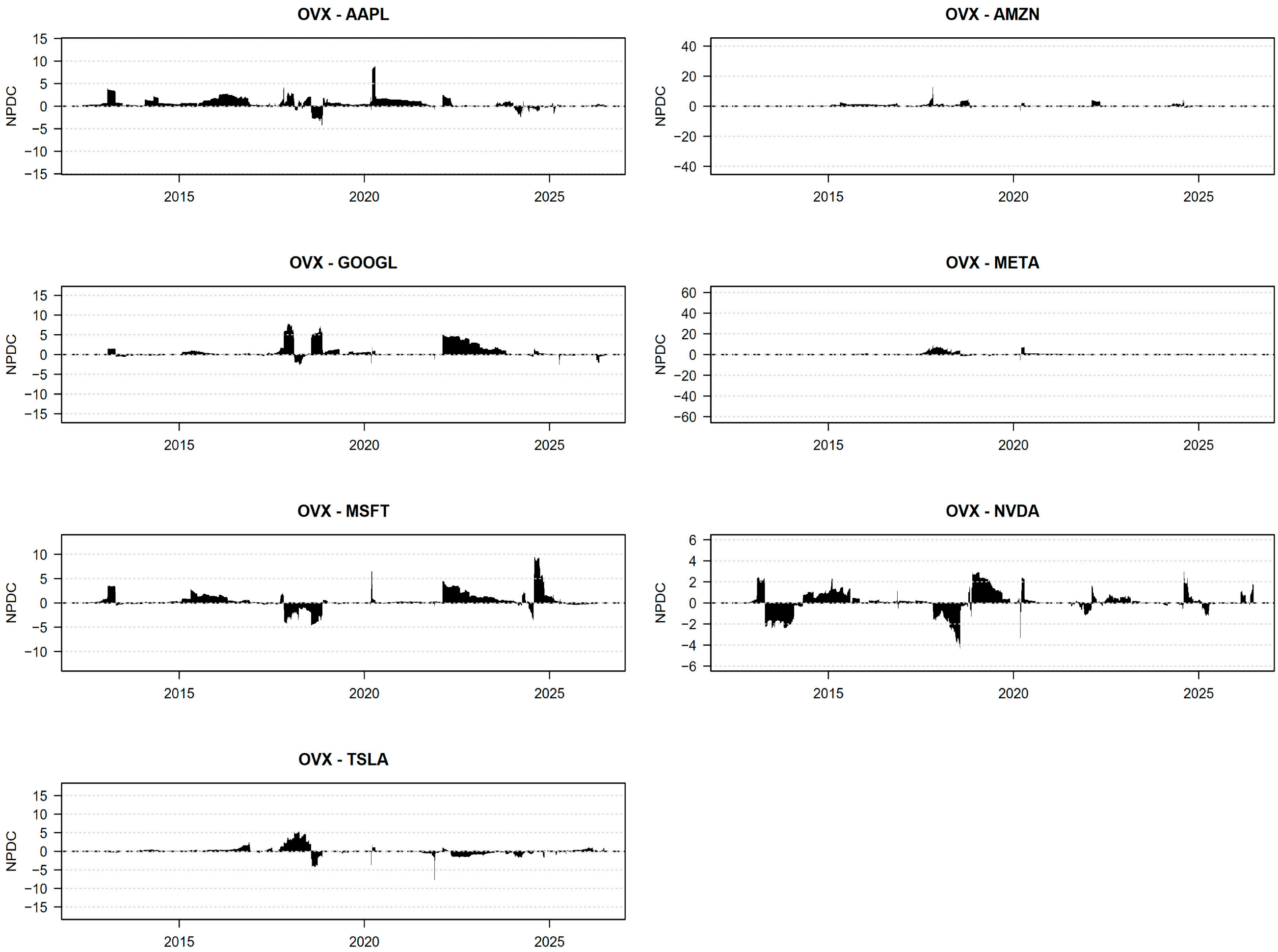

Figure 5. NPDC: OVX to Magnificent Seven Stocks.

Figure 5 presents the dynamic NPDC results between the OVX and the Magnificent Seven stocks. Positive values indicate dominant net volatility transmission from the OVX to the respective stock. Negative values indicate transmission from the stock to the OVX. The results show that pairwise transmission between changes in oil-market implied volatility and technology-stock volatility varied considerably over time. The OVX became a net transmitter during periods of positive values for the OVX–AAPL, OVX–GOOGL, and OVX–MSFT pairs. The occurrence of negative values shows that the direction was not constant. Transmission between the OVX and NVDA changed direction more frequently. The OVX–AMZN and OVX–META pairs generally remained around zero but displayed brief positive spikes. Negative values for OVX–TSLA indicate stronger transmission from Tesla to the OVX during certain periods. These heterogeneous patterns indicate that changes in oil-market uncertainty were not transmitted uniformly across the Magnificent Seven and that the direction of transmission depended on both the individual firm and prevailing market conditions. Overall, the OVX relationships exhibit a dynamic and bidirectional transmission structure rather than a persistent one-way flow of volatility from the oil market to technology stocks.

Figure 6 presents the dynamic NPDC results between the GVZ and the Magnificent Seven stocks. Positive values indicate dominant net volatility transmission from the GVZ to the respective stock. Negative values indicate transmission from the stock to the GVZ. The results show that pairwise transmission between changes in gold-market implied volatility and technology-stock volatility varied considerably over time. The positive values observed for GVZ–AAPL and GVZ–META, particularly after 2020, indicate that the GVZ became a net volatility transmitter. Negative values dominated the GVZ–AMZN relationship during 2020–2022, while positive values became more pronounced afterward. This pattern indicates a change in the direction of transmission. The transmitter role also shifted over time for the GVZ–GOOGL, GVZ–MSFT, and GVZ–NVDA pairs. The GVZ–TSLA relationship displayed lower absolute NPDC values and frequent directional changes. Overall, these heterogeneous patterns indicate that gold-market uncertainty was not transmitted uniformly across the Magnificent Seven and that the relationship between the GVZ and individual firms was dynamic and bidirectional.

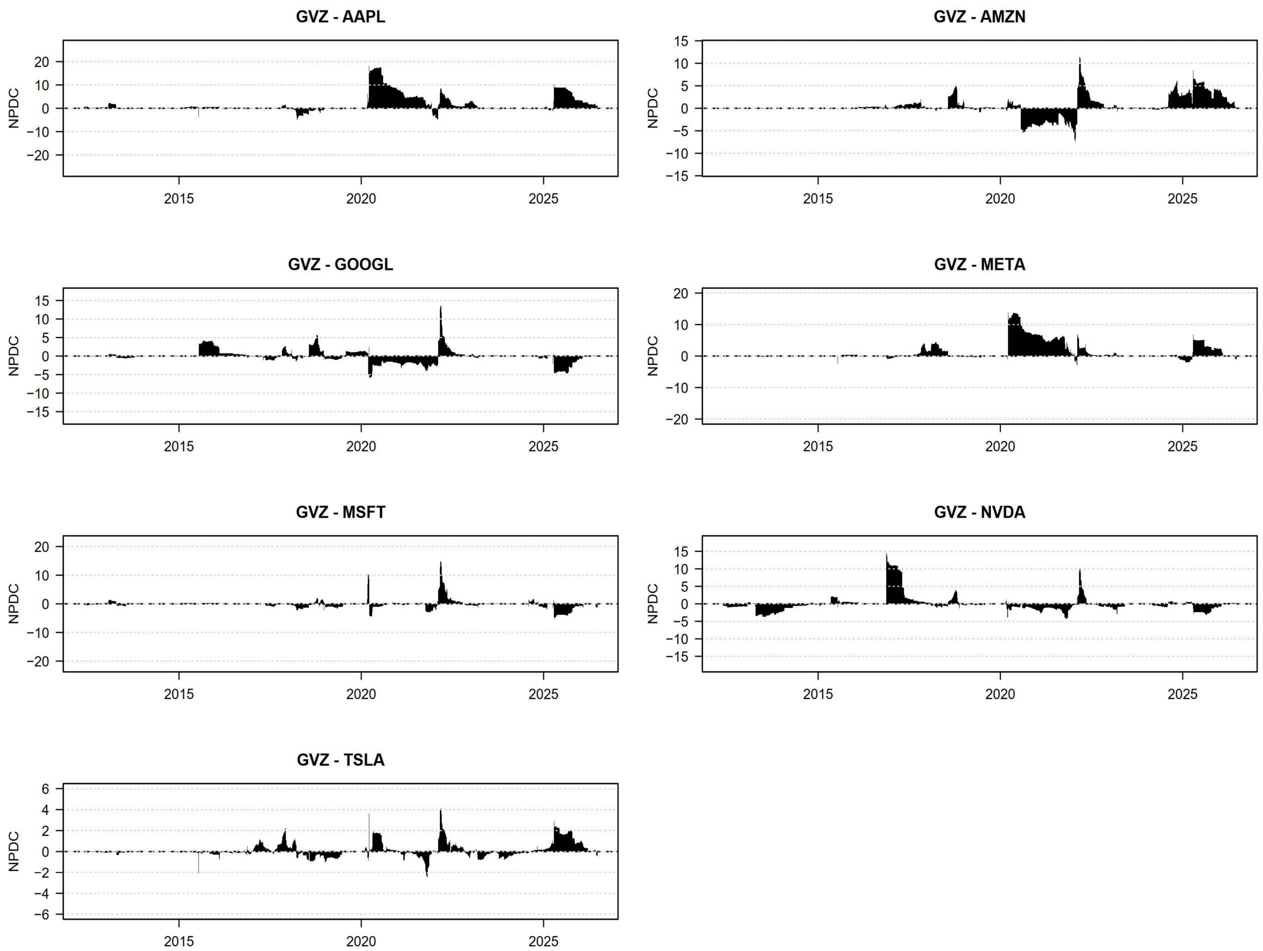

Figure 6. NPDC: GVZ to Magnificent Seven Stocks.

The NPDC results show that the direction and magnitude of volatility transmission vary considerably over time and across variable pairs. The dynamic NPDC results between the VIX, OVX, and GVZ and the Magnificent Seven companies indicate that the direction of transmission can change under different market conditions, with stronger bidirectional relationships emerging in certain periods. To improve readability and provide a quantitative summary of these dynamics, the main NPDC directions and magnitudes observed during selected periods are reported in Table A1 in Appendix A.

Figure 7 presents the average NPDC network between the global volatility indices and the Magnificent Seven stocks. Blue nodes represent net volatility transmitters, while yellow nodes represent net receivers. Node size is proportional to the absolute NET value. Arrows indicate the direction of net transmission, and line thickness reflects the relative strength of the average NPDC relationship. AAPL is the strongest net transmitter in the network, followed by META and AMZN. The main transmission channels extend from these companies to MSFT, NVDA, and GOOGL. MSFT and NVDA are the main net receivers, while GOOGL has a more limited receiver role. The relatively low net connectedness of the VIX, OVX, GVZ, and TSLA indicates more balanced transmitter and receiver roles. More importantly, the concentration of the strongest transmission channels among the Magnificent Seven reinforces the finding that system-wide connectedness is driven primarily by within-group spillovers rather than by cross-group transmission from the global volatility indices. This network structure is consistent with the connectedness results reported in Table 5.

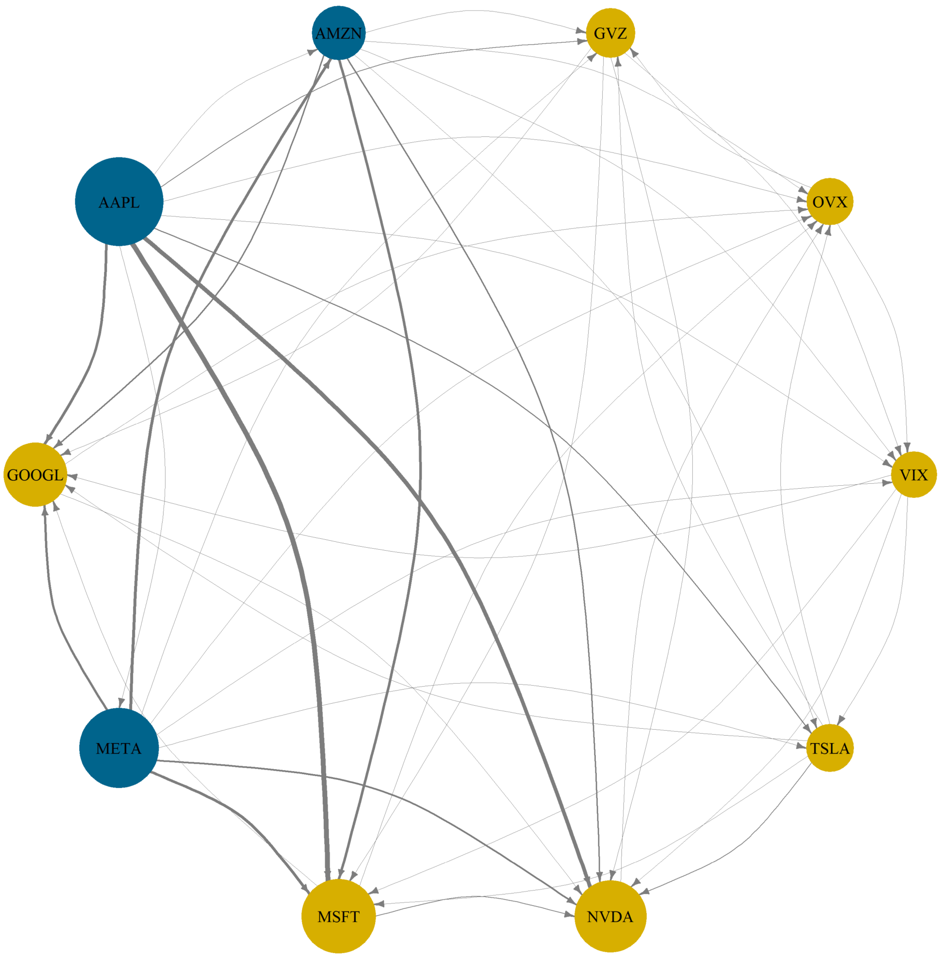

Figure 7. Average NPDC Network of Global Volatility Indices and Magnificent Seven Stocks. Note: Blue nodes indicate net transmitters, whereas yellow nodes indicate net receivers. Node size reflects the magnitude of volatility transmission TO the system. Edge thickness and darkness increase with the strength of directional connectedness, and arrows indicate the direction of transmission.

4.3. Robustness Analysis

Following the robustness strategies adopted in the time-varying financial connectedness literature, the sensitivity of the baseline findings is evaluated under alternative estimation settings and model specifications (Huang et al., 2023; Lu et al., 2024). In particular, Lu et al. (2024) assess the robustness of dynamic spillover estimates across alternative forecast horizons and competing connectedness specifications, while Huang et al. (2023) examine the stability of their main time-varying results under alternative empirical settings. Accordingly, the present study evaluates robustness using alternative forecast horizons (H = 5 and H = 20), an alternative lag specification (p = 2), and the generalized Diebold and Yilmaz (2012) rolling-window VAR framework with 200-day and 250-day rolling windows.

The results reported in Table 7 indicate that the main findings are largely insensitive to the forecast horizon and lag specification and remain broadly consistent under the alternative connectedness framework. Changing the forecast horizon from the baseline value of 10 days to 5 and 20 days produces only negligible changes in the average TCI, which remains close to 33%. Similarly, re-estimating the TVP-VAR model with two lags yields an average TCI of 33.42%, compared with 32.76% in the baseline specification. The dynamic TCI series obtained from the one- and two-lag specifications are highly correlated (0.9854), and the transmitter–receiver classification remains unchanged.

Table 7. Robustness Checks across Alternative Forecast Horizons, Lag Specifications, and the DY Rolling-Window Framework.

Measure	Baseline TVP-VAR	H = 5	H = 20	Lag = 2	DY VAR (200-Day)	DY VAR (250-Day)
Average TCI (%)	32.76	32.50	32.79	33.42	30.75	29.81
Main net transmitters	AAPL, META, AMZN	Same	Same	Same	Same	Same
Main net receivers	MSFT, NVDA, GOOGL	Same	Same	Same	Same	Same
Transmitter/receiver role changes	–	–	–	0	1 (VIX)	1 (VIX)
Dynamic TCI correlation with baseline	1.000	–	–	0.9854	0.7204	0.7009
Maximum TCI (%)	71.77	–	–	69.98	89.96	89.96
Peak date	19 March 2020	–	–	23 March 2020	17 July 2015	17 July 2015

Note: The baseline specification is the TVP-VAR connectedness model with a forecast horizon of 10 days and one lag. Robustness is assessed using alternative forecast horizons of 5 and 20 days, an alternative lag specification of two lags, and the generalized Diebold and Yilmaz (2012) VAR connectedness framework estimated using 200-day and 250-day rolling windows. Both DY specifications retain the baseline lag order and forecast horizon (lag = 1, H = 10). The correlation between the dynamic TCI series obtained from the 200-day and 250-day DY rolling-window specifications is 0.8744, and no transmitter–receiver role changes are observed between the two window lengths. “Same” indicates that the transmitter or receiver classification remains unchanged relative to the baseline specification.

Under the DY rolling-window specifications, the average TCI is somewhat lower than in the baseline TVP-VAR model, at 30.75% for the 200-day window and 29.81% for the 250-day window. The principal transmitter and receiver patterns nevertheless remain largely consistent with the baseline results. Under both rolling-window specifications, only VIX changes its net role relative to the baseline, from a marginal net receiver to a net transmitter. The dynamic TCI correlations with the baseline are 0.7204 and 0.7009 for the 200-day and 250-day windows, respectively. More importantly, the dynamic TCI series obtained from the two DY window lengths are strongly correlated (0.8744), and no transmitter–receiver role changes occur between the 200-day and 250-day specifications. Both specifications also identify the same maximum TCI and peak date. These results indicate that the main findings obtained under the DY framework are not materially driven by the choice of rolling-window length. Overall, the principal connectedness structure is robust across alternative forecast horizons, lag specifications, rolling-window lengths, and connectedness frameworks. However, the differences in TCI magnitude and peak timing between the TVP-VAR and DY specifications indicate some sensitivity to the estimation method.

5. Discussion

The findings reveal a moderate and time-varying level of volatility connectedness between the global volatility indices and the Magnificent Seven companies. The TCI increased during the COVID-19 pandemic, global inflationary pressures, and monetary tightening, indicating stronger volatility transmission during periods of market stress. This result is consistent with Ahmad et al. (2021), Z. Liu et al. (2021), Youssef et al. (2021), Long et al. (2022), Naeem et al. (2023), Xie et al. (2024), Bouteska et al. (2024), and Lu et al. (2024). Similar findings are reported by Gökgöz et al. (2025), Singh et al. (2025) and Gherghina et al. (2026). While previous studies mainly examine connectedness among stock markets, commodities, or volatility indices, the present study shows that volatility transmission between global volatility indices and the Magnificent Seven is also dynamic. More importantly, the decomposition results indicate that system-wide connectedness is driven primarily by spillovers within the Magnificent Seven rather than by cross-group transmission from the global volatility indices. In contrast, uncertainty originating from equity, oil, and gold markets plays a comparatively limited cross-group role. The external connectedness results further reveal modest net volatility transmission from the Magnificent Seven to the global volatility indices, implying that these companies are not merely recipients of external uncertainty but also contribute to volatility propagation across the broader financial system. However, the dynamic external connectedness results show that the relatively low external TCI over the full sample does not imply weak cross-group transmission in all periods. External connectedness strengthens markedly during the COVID-19 period and in 2022, when the Russia–Ukraine war and monetary tightening became prominent, while declining to lower levels during 2023–2024. This finding indicates that transmission between the global volatility indices and the Magnificent Seven, although limited on average, can temporarily strengthen depending on market conditions. Taken together, the evidence suggests that firm-level interactions within the Magnificent Seven play a more important role in shaping system-wide connectedness than direct spillovers from global uncertainty indicators. This finding highlights an important distinction that the total connectedness measure alone cannot reveal. A high level of system-wide connectedness does not necessarily imply equally strong cross-market transmission between the global volatility indices and the Magnificent Seven. The within-group and cross-group decomposition identifies how much of total connectedness originates from interactions within economically distinct groups and how much arises from transmission between them. The decomposition therefore complements the economic interpretation of standard connectedness measures by identifying not only the level of total connectedness but also the main source of volatility transmission within the system.

The directional connectedness results show that the Magnificent Seven companies perform heterogeneous roles within the system. Apple, Meta, and Amazon emerged as the main net volatility transmitters, whereas Microsoft, Alphabet, and NVIDIA generally acted as net receivers. This pattern is broadly consistent with BenSaïda et al. (2022), Shahid et al. (2023), and Arı et al. (2024). While Arı et al. (2024) identify only Amazon as a leading transmitter, the present study also identifies Apple and Meta. This difference may reflect differences in the sample period and the variables included in the analysis. Similarly, the receiver roles of Microsoft, Alphabet, and NVIDIA are consistent with Khan et al. (2025), who report that information technology companies exhibit varying exposure to external uncertainty shocks.

The NPDC results confirm that pairwise volatility transmission is time-varying. The stronger spillovers from the VIX to Apple and Meta during the COVID-19 pandemic, together with changes in transmission direction across several stock pairs, are in line with Antonakakis et al. (2023), F. Liu et al. (2023), Naeem et al. (2023), and Yoon et al. (2026), who also report that volatility transmission evolves with changing market conditions.

The structural characteristics of the VIX should be considered when evaluating its connectedness with the Magnificent Seven. The VIX is derived from S&P 500 index options (Whaley, 2009), and the combined weight of the Magnificent Seven in the S&P 500 exceeded

31% as of October 2024 (S&P Dow Jones Indices, 2024). This structural overlap implies that the estimated connectedness may reflect not only market-wide risk perceptions but also common market movements arising from the influence of these companies on the S&P 500 and the feedback between them. Accordingly, the VIX should be interpreted as a market-based risk indicator that interacts with the Magnificent Seven rather than as a purely exogenous uncertainty shock.

The strong within-group connectedness among the Magnificent Seven companies can be explained through several economic channels. First, their large size and growth-oriented characteristics may expose them similarly to common factors such as interest rates, discount rates, investor sentiment, and expectations about the technology sector. This common exposure may lead to joint repricing and facilitate the transmission of firm-level volatility shocks within the group, particularly during periods of heightened macroeconomic uncertainty. This interpretation is consistent with Umar et al. (2025), who document strong return and volatility connectedness among the Magnificent Seven and show that transmitter–receiver roles vary with market conditions.

Second, the Magnificent Seven companies operate in different but interconnected segments of the same technology ecosystem. Complementarities across artificial intelligence, semiconductors, cloud computing, and data-center infrastructure may allow changes in expectations surrounding one company or business segment to affect the growth and investment expectations of other firms. The rapid expansion of generative artificial intelligence after 2023, together with increased investment in semiconductors, cloud computing, and data-center infrastructure, may have strengthened the economic linkages among these companies (Umar et al., 2025; Aslam, 2026). From this perspective, the volatility transmission observed from NVIDIA to Meta, Amazon, Microsoft, and Apple during certain periods may be related to NVIDIA's central position in the AI infrastructure and semiconductor ecosystem. Aslam (2026) also identifies an important intermediary role for NVIDIA in volatility transmission among AI-related stocks.

Third, exposure to common business activities, index membership, and passive investment flows may provide additional channels through which volatility is transmitted among the Magnificent Seven companies. Volatility transmission between Amazon and Meta may be related to their exposure to common areas such as digital platforms, online consumer demand, and advertising markets. In addition, the large market capitalizations of the Magnificent Seven and their high weights in major stock market indices may allow index-based fund flows and portfolio rebalancing to generate simultaneous price movements across several companies. Previous studies show that index membership can increase co-movement among stocks and that ETF trading can strengthen return correlations (Barberis et al., 2005; Da & Shive, 2018). Tesla's inclusion in the S&P 500 in December 2020 further supports the relevance of this channel for the present sample (S&P Dow Jones Indices, 2020). Part of the stronger transmission observed between Tesla and other large technology companies after 2020 may therefore be associated with common index movements and passive investment flows. These explanations should, however, be viewed as potential economic mechanisms consistent with the observed volatility transmission patterns; the TVP-VAR connectedness results do not establish structural causal relationships among these channels.

The findings have several implications for portfolio and risk management. First, the high within-group connectedness among the Magnificent Seven suggests that holding these stocks together in the same portfolio may provide more limited diversification benefits than expected, particularly during periods of market stress. Portfolio managers should therefore consider not only firm-level volatility but also time-varying volatility transmission across firms. Second, the relatively low cross-group connectedness between the global volatility indices and the Magnificent Seven suggests that including assets exposed to different sources of risk may offer potential diversification and hedging benefits. These benefits should not be assumed to remain constant, however, because connectedness varies with market conditions. The external TCI of 6.15%, which is substantially lower than the system-wide TCI of 32.76%, indicates that most volatility transmission originates within the system rather than between the two groups. For institutional portfolio managers, this distinction suggests that tail-risk protection in portfolios concentrated in Magnificent Seven stocks should not rely solely on diversification within the group. Considering asset classes exposed to different sources of risk and monitoring cross-group connectedness over time may help identify potential hedging instruments during periods of heightened market stress. Since the present analysis does not estimate optimal hedge ratios or portfolio weights, these findings should not be interpreted as direct evidence of the effectiveness of a specific hedging strategy, but rather as empirical evidence of the importance of considering cross-asset connectedness in tail-risk management.

Third, monitoring net volatility transmitters such as Apple, Meta, and Amazon may help portfolio and risk managers identify potential sources of volatility pressure within the system. From a financial stability perspective, the findings suggest that large technology companies should not be viewed solely as recipients of global uncertainty shocks. The limited net external transmission observed from the Magnificent Seven to the global volatility indices suggests that volatility developments in large technology companies may also be usefully monitored alongside broader market risk indicators. Although these findings do not directly support any specific regulatory intervention, they highlight the importance of considering concentration risk and common volatility dynamics among large-cap technology companies in financial stability assessments.

The robustness analysis confirms that the overall connectedness structure and the main transmitter–receiver classifications remain broadly stable across alternative forecast horizons, lag specifications, rolling-window lengths, and the DY connectedness framework. Overall, these results indicate that connectedness intensifies during periods of market stress and that the roles of individual variables evolve over time.

6. Conclusions

This study examines the dynamic connectedness between global volatility indices (VIX, OVX, and GVZ) and the stock volatilities of the Magnificent Seven companies using the TVP-VAR connectedness approach. The results show that system-wide connectedness is driven primarily by spillovers within the Magnificent Seven rather than by direct cross-group transmission from global volatility indices. This finding suggests that firm-level interactions among large technology companies play a central role in volatility propagation, whereas uncertainty originating from equity, oil, and gold markets exerts a comparatively limited direct cross-group influence. Volatility transmission varies over time and intensifies during periods of heightened financial uncertainty, including the COVID-19 pandemic, global inflationary pressures, and monetary policy tightening. Apple, Meta, and Amazon emerged as the main net volatility transmitters, whereas Microsoft, Alphabet, and NVIDIA generally acted as net receivers. The NPDC results further show that the direction and magnitude of pairwise volatility transmission vary across market conditions, and the main findings remain broadly robust across alternative forecast horizons, lag specifications, and the DY rolling-window connectedness framework.

The main economic implication of these findings is that system-wide connectedness should not be viewed solely as a result of global uncertainty transmission to large technology companies. The dominance of within-group connectedness indicates that a substantial share of volatility transmission originates from interactions among the Magnificent Seven companies themselves. Their different transmitter and receiver roles also suggest that the

Magnificent Seven should not be treated as a homogeneous group in risk management and financial stability assessments.

The findings provide more specific implications for investors, portfolio managers, and authorities responsible for financial stability. For investors and portfolio managers, the strong within-group connectedness among the Magnificent Seven suggests that the diversification benefits of holding these stocks together may decline, particularly during periods of market stress. Portfolio allocation should therefore consider not only the individual risk characteristics of these companies but also the time-varying volatility transmission among them. The relatively limited cross-group connectedness between the global volatility indices and the Magnificent Seven suggests that including assets exposed to different sources of risk may provide potential diversification and hedging benefits; however, these benefits should not be assumed to remain constant because connectedness varies over time. From a financial stability perspective, monitoring net volatility transmitters such as Apple, Meta, and Amazon, together with within-group connectedness among the Magnificent Seven, may help assess volatility pressures originating from large technology companies. Although the findings do not directly support any specific regulatory intervention, they suggest that policymakers and regulatory authorities may benefit from considering concentration risk and dynamic volatility linkages among large technology companies alongside global risk indicators in financial stability assessments.

This study has several limitations. First, the analysis is restricted to the VIX, OVX, GVZ, and the Magnificent Seven companies, limiting the generalizability of the findings to other uncertainty sources, sectors, and markets. Second, volatility is represented by squared daily logarithmic returns, whereas alternative measures may better capture intraday or latent volatility dynamics. Third, the TVP-VAR connectedness framework identifies dynamic forecast-error variance linkages but does not establish structural causality. Finally, although the robustness analysis considers alternative forecast horizons, lag specifications, and the DY rolling-window framework, it does not cover all possible model specifications or connectedness approaches.

Future research may extend this framework by incorporating additional uncertainty indicators, alternative volatility indices, and companies from other sectors or markets. Alternative group structures could provide further evidence on within-group and cross-group transmission. Studies using higher-frequency data, realized volatility measures, or model-based volatility estimates may assess the sensitivity of the findings to alternative volatility proxies. Future research may also apply alternative connectedness methods, quantile- or frequency-based approaches, and structural identification strategies to examine volatility transmission under different market conditions and its underlying causal mechanisms.

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Data Availability Statement: The VIX, OVX, and GVZ data used in this study are publicly available from the Chicago Board Options Exchange (CBOE) at the VIX Historical Data, OVX Index Dashboard, and GVZ Index Dashboard, respectively. The stock price data for the Magnificent Seven (Apple, Amazon, Alphabet, Meta Platforms, Microsoft, NVIDIA, and Tesla) are publicly available from Investing.com. All data sources were accessed on 29 June 2026. The processed dataset used in the analysis is available from the author upon reasonable request. Cboe VIX: https://www.cboe.com/tradable-products/vix/vix-historical-data/; Cboe OVX: https://www.cboe.com/us/indices/dashboard/ovx/; Cboe GVZ: https://www.cboe.com/us/indices/dashboard/gvz/; Magnificent Seven stock price data: https://www.investing.com/.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Additional Connectedness Figures

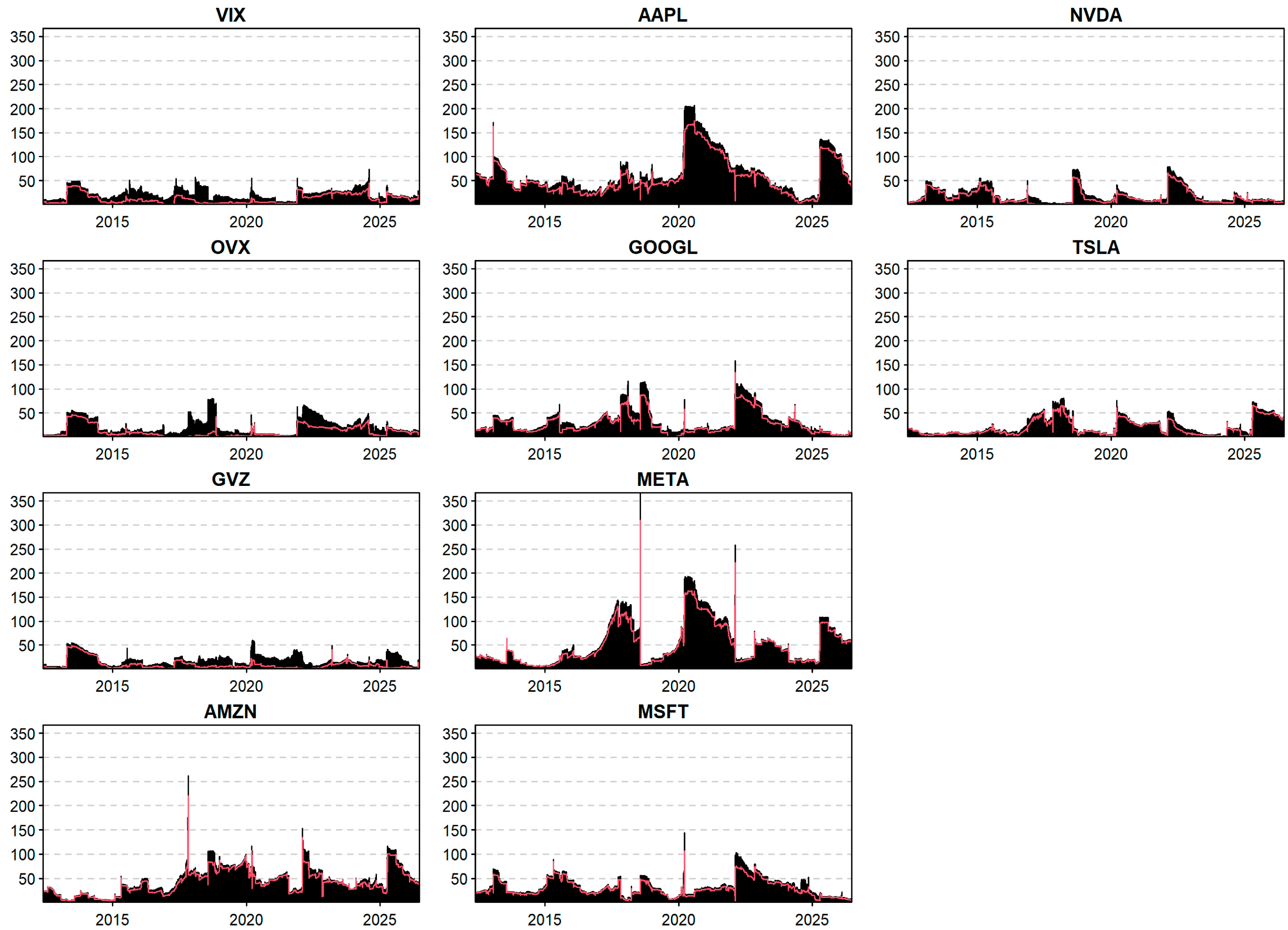

Figure A1. Dynamic Total and Within-Group TO Connectedness. Note: The black shaded areas represent total TO connectedness, while the red lines represent within-group TO connectedness.

Table A1. NPDC summary.

Period	Index	Stock	Peak NPDC	Peak Date	Direction
1 February 2020–31 December 2021	VIX	AAPL	15.11	19 March 2020	VIX → AAPL
1 February 2020–31 December 2021	OVX	TSLA	13.70	26 November 2021	TSLA → OVX
1 February 2020–31 December 2021	GVZ	AAPL	21.79	19 March 2020	GVZ → AAPL
24 February 2022–31 December 2022	VIX	AMZN	6.75	27 April 2022	VIX → AMZN
24 February 2022–31 December 2022	OVX	GOOGL	4.91	24 February 2022	OVX → GOOGL
24 February 2022–31 December 2022	GVZ	MSFT	15.01	4 March 2022	GVZ → MSFT
1 January 2023–31 December 2024	VIX	NVDA	10.34	5 August 2024	NVDA → VIX
1 January 2023–31 December 2024	OVX	MSFT	10.30	13 August 2024	OVX → MSFT
1 January 2023–31 December 2024	GVZ	AMZN	8.62	8 November 2024	GVZ → AMZN
1 January 2025–25 June 2026	VIX	GOOGL	8.49	9 April 2025	GOOGL → VIX
1 January 2025–25 June 2026	OVX	GOOGL	2.65	9 April 2025	GOOGL → OVX
1 January 2025–25 June 2026	GVZ	AAPL	10.63	16 April 2025	GVZ → AAPL

https://doi.org/10.3390/economies14090391

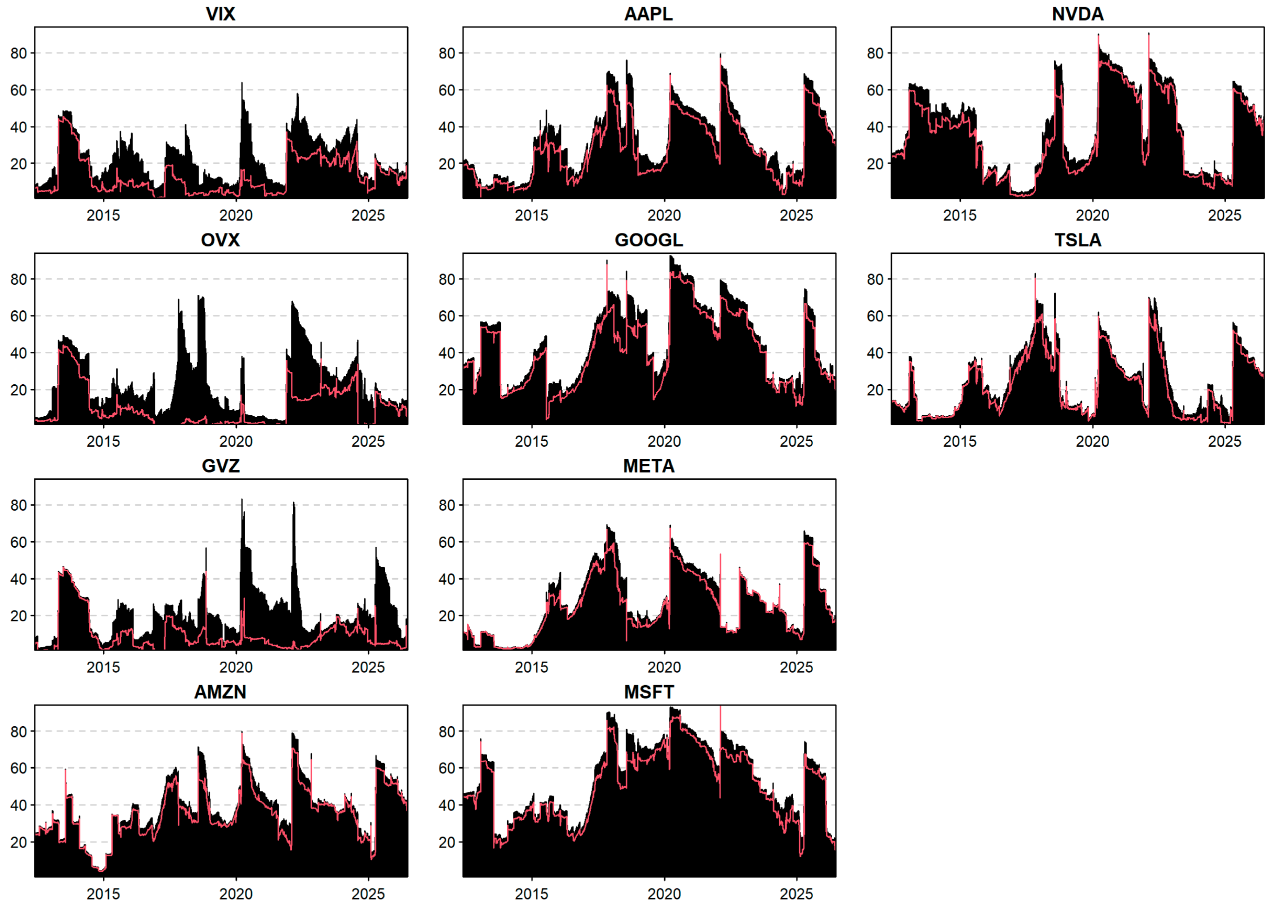

Figure A2. Dynamic Total and Within-Group FROM Connectedness. Note: The black shaded areas represent total FROM connectedness, while the red lines represent within-group FROM connectedness.

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