CO-JUMP BEHAVIOR AND MARKET SHOCKS: EVIDENCE FROM FAANG STOCKS

Daouia Chebab[1]✉, Mukhriz İzraf Azman Aziz[2], Norzalina Ahmad[2]

[1] *University of Bahrain, Sakhir, Kingdom of Bahrain*
[2] *Universiti Utara Malaysia, Sintok, Malaysia*

EUROPEAN JOURNAL OF BUSINESS SCIENCE AND TECHNOLOGY

Volume 12 Issue 1
ISSN 2694-7161
www.ejobsat.com

ABSTRACT

Technology stocks like Facebook, Apple, Amazon, Netflix, and Google, collectively referred to as FAANG stocks, are among the most systemically important equities in global markets, attracting international investors due to the extensive use of technology in day-to-day business. However, these stocks are considered risky assets, so building an optimal portfolio requires effective risk management. To address this, this study examines the jump and co-jump behavior of the FAANG stocks over the period 2012–2026. Jumps are identified using a standardized residual approach in which daily returns that deviate from GARCH (1,1), as well as estimated conditional volatility by more than three standard deviations, are classified as jump events, based on Laurent et al.'s (2016) conceptual framework. Co-jump activity is assessed using a co-exceedance threshold rule and logistic regression, which is in line with the larger co-jump literature (Dungey and Hvozdyk, 2011; Bouri et al., 2020). Results highlight the presence of jump and co-jump activity within the FAANG stocks, where Google and Amazon exhibited the highest co-jump connectedness, revealing their vital role in spreading economic shocks across the FAANG network. In contrast, Netflix appeared to be a more peripheral asset with lower co-jump centrality. Jumps occur during macro stress periods, most notably the 2018 US-China trade war, the COVID-19 pandemic in 2020, and the 2022 rate-hike cycle, and are generally negative in direction, indicating asymmetric downside risk. Our findings are directly relevant to global investors, asset managers, and portfolio managers. Policymakers may use these outcomes to construct a stronger framework for improving financial stability and mitigating systemic risk during market stress periods.

KEY WORDS

jump behavior, co-jump, FAANG stocks, volatility, systemic risk

JEL CODES

G11, G14, G15, C58

CHEBAB, Daouia, AZMAN AZIZ, Mukhriz İzraf, and AHMAD, Norzalina. 2026. Co-Jump Behavior and Market Shocks: Evidence from FAANG Stocks. *European Journal of Business Science and Technology,* 12 (1): 33–46. ISSN 2694-7161, DOI 10.11118/ejobsat.2026.006.

1 INTRODUCTION

Jump analysis is among the most powerful tools available for characterizing extreme price dynamics in financial markets. Stock prices sometimes display rapid and considerable movements known as 'jumps', abrupt fluctuations triggered by unexpected news, economic events, or shifts in market sentiment (Johnson et al., 2022). Co-jump analysis extends this by examining cases where multiple assets experience extreme price movements simultaneously, capturing systemic co-movement driven by common economic shocks (Peng and Yao, 2022). Co-jumps are particularly consequential for risk management because they represent extreme simultaneous losses across correlated assets. They can render conventional portfolio diversification strategies ineffective precisely when protection is most needed.

While substantial literature examines jumps in traditional asset classes, including equities, Treasury bonds, commodities, and cryptocurrencies, the co-jump dynamics of FAANG stocks remain largely unexplored. The FAANG companies—Facebook (Meta), Apple, Amazon, Netflix, and Google (Alphabet)—collectively emerged as dominant forces in global equity markets from the mid-2010s onward[1]. The FAANG companies represent the most concentrated cluster of systemically important equities in modern financial markets, with a joint market capitalization of approximately $9 trillion as of Q2 2024 (FactSet, 2024) and a combined weight of 17.3% in the S&P 500 index (S&P Global Market Intelligence, 2024). This study addresses this gap directly by providing the first comprehensive analysis of jump and co-jump behavior across all five FAANG stocks over the 2012–2026 period.

Monitoring price jumps in FAANG stocks is critical for several reasons. First, their dominant index weights mean that idiosyncratic jumps in these stocks can propagate into systemic risk for index-tracking investors. Second, their high trading volumes and widespread analyst coverage make them natural focal points for information-driven price discontinuities. Third, their common macro-sensitivities to interest rates, geopolitical events, and regulatory risk can lead to linked extreme movements, or co-jumps, which have direct consequences for portfolio risk. We select the five FAANG stocks because they represent the most systemically important technology cluster in global equity markets and have continuous, high-quality daily data available from May 2012 onward, with the start date determined by Facebook's IPO on May 18, 2012.

Co-jump analysis is relevant in the case of widely traded and very important stocks such as those in the FAANG group. Facebook rebranded as Meta in 2021, while Google reorganized under Alphabet in 2015.[2] Furthermore, there is widespread evidence that publicly listed FAANG stocks have a significant impact on global markets through job creation, people networks, goods supply, and entertainment production. The systemic importance of these companies extends beyond the technology sector. Their supply chain dependencies and cross-sector financial linkages create exposure to the energy (approximately 3% supplier overlap), industrial (8%), and financial (10%) sectors (Saleem et al., 2023). These interconnections amplify shock transmission during periods of extreme price movements, as captured by co-jump analysis.

This study uses a semi-parametric jump detection procedure inspired by the conceptual framework of Laurent et al. (2016), implemented using a standard GARCH (1,1) specification for the conditional variance, followed by co-exceedance rules, logistic regression, and network analysis to examine the co-occurrence and propagation of jumps across FAANG assets. Understanding the jump dynamics of these technology companies is crucial, given their out-

[1] The FAANG acronym was popularized by CNBC commentator Jim Cramer in 2013 (initially as FANG: Facebook, Amazon, Netflix, Google); Apple was added to form FAANG by 2017 (Ali et al., 2025).

[2] In this paper, we use the legacy company names (Facebook, Amazon, Apple, Netflix, Google), and the FAANG acronym is retained throughout.

sized importance in modern financial markets and the concentration risk they represent for broadly held portfolios.

Reviewing the existing literature reveals that FAANG stocks have been largely analyzed from performance, competition, and technology innovation perspectives (Sen and Chakrabarti, 2023; Saleem et al., 2023; de Almeida, 2020). Although some studies have investigated jump and co-jump behavior in other asset classes, our research is among the first to do so specifically for FAANG stocks. The main contributions of this paper are threefold: (1) we provide the first systematic documentation of jump and co-jump frequencies across all five FAANG stocks over a 13-year window spanning multiple market regimes; (2) we characterize the network structure of FAANG co-jump dependencies; and (3) we identify macro-level determinants of FAANG jump probability using VIX, market returns, and event-specific dummies.

The remainder of this paper follows this structure. Section 2 presents the literature review, while Section 3 presents the data and methodological approach. Section 4 presents jump detection results, co-jump analysis, and the new macro determinants analysis. Section 5 provides the conclusion.

2 LITERATURE REVIEW

The FAANG companies (Facebook, Apple, Amazon, Netflix, and Google) have concentrated market impact and shared technological infrastructure have attracted substantial academic interest, particularly regarding their return dynamics and extreme price behavior. The literature relevant to this study spans three streams: asset price jumps, co-jump analysis, and FAANG-specific research.

Barndorff-Nielsen and Shephard (2006) define jump activity as a vital element of asset pricing, whereas Bates (2000) affirms that crash risk can be reflected by jump activity. Understanding and examining the jump activity of any asset has gained growing attention from investors, academics, and practitioners due to its important implications for asset allocation, derivatives pricing, and risk management. Dungey and Hvozdyk (2011) utilized high-frequency Treasury data in the US to investigate co-jump behavior in current and futures prices, finding that the probability of co-jumping changes around scheduled macroeconomic announcements. In a similar vein, Lahaye et al. (2011) connected co-jumps from a panel of US stocks to macroeconomic announcements.

Driessen and Maenhout (2013) studied jump and volatility risk in international market integration using index options, finding significant evidence for volatility risk and jump pricing in local markets. Oliva and Renò (2018) examined co-jump risk in dynamic portfolio problems and confirmed the importance of price jumps in portfolio optimization. Clements and Liao (2017) utilized a set of jump and co-jump investigation approaches to show how index-level jumps and co-jumps among component stocks can predict index-level return variance.

Recent studies on co-jumping have increased in scope and application. Baruník and Fišer (2019) studied the European and US Treasury yield curves and confirmed that co-jumps are significantly affected by monetary policy announcements. Bonaccolto et al. (2021) examine co-jumps across the cross-section of US equities and identify high-capitalization technology stocks as disproportionate contributors to systemic co-jump events, a finding directly relevant to our FAANG analysis. Bouri et al. (2020) checked the presence of jump behavior in 12 cryptocurrency returns and confirmed that co-jumping behavior is correlated with rises in trading volume. Peng and Yao (2022) develop improved co-jump tests and provide Monte Carlo evidence on their finite-sample performance, demonstrating that threshold-based co-exceedance rules, such as the one we employ, have reliable power in samples of moderate size.

The existing literature on FAANG stocks focuses primarily on their performance and technical analysis. De Almeida (2020) demonstrated that standard technical analysis indicators (Ichimoku, MACD, RSI) yield actionable signals for FAANG stocks, confirming that these stocks are amenable to rigorous empirical analysis. Sen and Chakrabarti (2023) document risk, volatility, and bubble episodes in FAANG portfolios. Saleem et al. (2023) examine FAANG stocks alongside gold and Islamic equity during COVID-19, providing evidence of their elevated systematic risk during the pandemic period. Despite this growing body of work, no prior study has systematically examined the co-jump dynamics of FAANG stocks as a group, and this gap motivates the present analysis.

3 DATA AND METHODOLOGY

3.1 Data

This study uses daily adjusted closing price and trading volume data for five leading technology stocks, collectively known as the FAANG stocks: Facebook, Apple, Amazon, Netflix, and Google. Data were obtained from Yahoo Finance (`https://finance.yahoo.com`), covering the period from May 18, 2012, through April 1, 2026. The sample period was determined by the earliest date of simultaneous data availability for all five stocks. Facebook completed its IPO on May 18, 2012, making this the natural start date. The 13-year window encompasses seven distinct market regimes: the post-financial crisis recovery (2012–2014), the 2015–2016 equity correction, the 2018 US–China trade war, the COVID-19 pandemic shock (2020), the post-pandemic inflation and rate-hike cycle (2021–2023), the AI-driven technology rally (2023–2024), and the renewed market volatility driven by global trade policy uncertainty (2025–2026). This breadth ensures that our findings are not specific to any single market environment.

Our empirical analysis relies on log returns, multiplied by 100 to simplify interpretation. To verify that each return series satisfies the stationarity condition required for GARCH-based conditional variance modeling, we apply the Augmented Dickey-Fuller (ADF) test. The results, summarized in Tab. 1, confirm that all return series are stationary at the 1% significance level, indicating their stability over time. All p-values below 0.0001 are reported as '< 0.0001' to avoid the misleading implication of an exact zero probability.

Tab. 1 also details key statistical properties of the returns. Netflix showed the highest average daily return (0.0013), followed by Amazon and Google (0.0009 each), while Apple and Facebook had the lowest mean return (0.0008 each). Netflix displayed the highest volatility (standard deviation = 0.029), while Apple had the lowest (0.0178). The skewness values were mostly negative, indicating returns tended toward losses, except for Amazon and Google, which had slight positive skewness. Significant excess kurtosis is evident for all

Tab. 1: Daily return statistical features (May 2012 – April 2026)

	Apple	**Amazon**	**Google**	**Facebook**	**Netflix**
Mean	0.0008	0.0009	0.0009	0.0008	0.0013
Max.	0.1426	0.1322	0.1506	0.2594	0.3522
Min.	−0.1377	−0.1514	−0.1237	−0.3064	−0.4326
Std. Dev.	0.0178	0.0202	0.0173	0.0250	0.0290
Skewness	−0.2020	0.0304	0.1308	−0.4071	−0.5058
Kurtosis	9.6626	8.9532	9.7046	24.4088	32.4957
p-value ADF test	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
p-value ARCH-LM test	< 0.0001	< 0.0001	< 0.0001	0.0090	0.0025

Note: p-values below 0.0001 reported as '< 0.0001' (blue) per revised reporting convention.

stocks, notably Netflix and Facebook, indicating a higher frequency of extreme price movements than under a normal distribution. The ARCH-LM test results (Engle, 1982) indicate conditional heteroscedasticity across all return series, confirming that a GARCH specification is appropriate.

Tab. 2 reports the Pearson correlation matrix of FAANG stock returns, ranging from 0.312 (Netflix and Apple) to 0.610 (Google and Amazon). Amazon is found to have a strong positive correlation with Google (0.610), while the correlation between Apple and Netflix is the weakest (0.312). These correlations imply limited diversification benefit within FAANG portfolios, particularly during market turbulence.

3.2 Methodology

This study investigates the presence of jumps and co-jumps in the returns of FAANG assets. Drawing on the conceptual framework of Laurent et al. (2016), we implement a simplified semi-parametric jump detection procedure. Unlike the original Laurent et al. (2016) approach, which employs a Bounded Innovation Propagation (BIP-GARCH) specification to prevent jump contamination of volatility estimates, we use a standard GARCH (1,1) model for computational tractability. This simplification is motivated by our primary objective of detecting jumps rather than precisely estimating the volatility process, and is acknowledged as a limitation. Our analysis proceeds in two main stages: jump detection in individual asset returns, followed by co-jump analysis across assets.

3.2.1 Testing for Jumps

We begin by estimating the conditional mean of the asset returns using either an autoregressive AR (p) process or a simple OLS with a time trend, defined as follows:

Step 1: Estimation of Conditional Mean

The conditional mean μ_t. The asset returns are estimated using either an autoregressive AR (p) model or a simple time trend with ordinary least squares (OLS). The model is described as follows:

$$r_t = \mu_t + \sum_{i=1}^{p} \zeta_i r_{t-i} + \epsilon_t, \tag{1}$$

where r_t represents the asset return at a time t, the μ_t is the conditional mean, ζ_i refers to the autoregressive coefficients for the lag i and lastly ϵ_t is the error term.

Using Time Trend (OLS) the equation is written as follows:

$$\mu_t = b_0 + b_1 t, \tag{2}$$

where b_0, b_1 refer to the parameters of the time trend estimated via OLS, and the residuals are calculated using the following formula:

$$\text{ar\_resid} = r_t - \mu_t. \tag{3}$$

Step 2: Conditional Volatility Modeling

In this step, we model the conditional volatility (σ_t^2) using a standard GARCH (q, q) model:

$$\begin{aligned} \sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2, \\ i &= 1, 2, \ldots, q, \end{aligned} \tag{4}$$

Tab. 2: Pairwise Pearson Correlation Matrix of FAANG Returns

	Apple	**Amazon**	**Google**	**Facebook**	**Netflix**
Apple	1				
Amazon	0.490	1			
Google	0.539	0.610	1		
Meta	0.428	0.519	0.529	1	
Netflix	0.312	0.450	0.384	0.351	1

Note: Sample period May 18, 2012 – April 1, 2026. All correlations are statistically significant at $p < 0.01$.

where σ_t^2 represents the conditional variance at time t, ω refers to constant, α_i refers to coefficients for lagged squared residuals (ϵ_{t-i}^2), β_i represents coefficients for lagged variances (σ_{t-i}^2).

Then, the conditional standard deviation is calculated as follows:

$$\sigma_t = \sqrt{\sigma_t^2} \tag{5}$$

While the original Laurent et al. (2016) method includes a leverage effect term in the GARCH model, represented as $\theta I_{t-1}\epsilon_{t-1}^2$, we chose to omit this component for computational simplicity, given that our primary goal is to detect jumps rather than precisely estimate volatility using the GJR-GARCH model.

Standardized Returns and Jump Detection

Next, the standardized returns $(\tilde{J}_t)$ are calculated as:

$$\tilde{J}_t = \frac{r_t - \mu_t}{\sigma_t} \tag{6}$$

Jumps are detected when the absolute value of the standardized return exceeds a threshold (λ), set at 3.0:

$$I_t = \begin{cases} 1, & \text{if } |\tilde{J}_t| > \lambda, \\ 0 & \text{otherwise,} \end{cases} \tag{7}$$

where I_t is the jump indicator variable.

3.2.2 Co-Jumping Analysis

After identifying individual asset jumps, we analyze the co-occurrence of jumps across the FAANG assets. We use two complementary methods: a co-exceedance rule and logistic regression. The attribution of these methods follows the co-jump literature (Dungey and Hvozdyk, 2011; Bouri et al., 2020; Clements and Liao, 2017) rather than any single reference; the threshold-based approach is not to be confused with the volatility forecasting framework of Ma et al. (2019).

Co-Exceedance Method

A co-jump event is defined as any trading day on which at least $n = 3$ of the five FAANG assets simultaneously exhibit a detected jump:

$$\begin{aligned} &\sum I\left(\text{Jump}_{i,t} > 0\right) = \\ &= \begin{cases} n_{\text{cojump}}, & \text{if } n \geq 3, \\ 0 & \text{otherwise,} \end{cases} \end{aligned} \tag{8}$$

where $I\left(\text{Jump}_{\ i,t} > 0\right)$ is an indicator of a jump in the asset i at time t_e, n refers to the threshold for simultaneous jumps $(n = 3)$, and n_{cojump} counts of co-jump days. This threshold-based co-exceedance rule (Equation 8) constitutes our primary co-jump definition. The threshold $n = 3$ requires a majority of FAANG assets to jump simultaneously, reducing spurious co-jump detection from unrelated idiosyncratic events while remaining sensitive to systemic shocks. We also generate a detailed co-jump table containing individual jump indicators for all assets on co-jump days.

Logistic Regression

To further characterize co-jump behaviour, we estimate logistic regressions where the jump indicator for each asset is modelled as a function of contemporaneous jump indicators for the other assets:

$$\begin{aligned} &\log\left(\frac{P\left(Y_t = 1 \mid X_t\right)}{1 - P\left(Y_t = 1 \mid X_t\right)}\right) = \\ &= \beta_0 + \sum_i \beta_i X_{i,t} + \epsilon_t, \end{aligned} \tag{9}$$

where Y_t is the binary jump indicator for the target asset, and $X_{i,t}$ are jump indicators for peer assets. We note explicitly that, because this regression is estimated on contemporaneous indicators, the results capture co-movement associations rather than causal or lead-lag dynamics.

Co-Jump Network Graph

Co-jump interdependencies are represented through a weighted network structure, where each node $i \in \mathbb{N}$ corresponds to a FAANG asset. Edge weights are defined as

$$w_{ij} = \sum_{t=1}^{T} I_t(i) I_t(j), \tag{10}$$

where $I_t(i)$ is a binary indicator equal to one if the asset i experiences a jump at a time t, and zero otherwise. This specification captures the total number of synchronous jump occurrences between asset pairs. Node size is scaled by the marginal jump intensity, $\sum_{t=1}^{T} I_t(i)$, providing a visual proxy for individual asset jump activity. Edge thickness and color intensity are mapped to w_{ij}, with higher values indicating stronger co-jump linkages. The viridis colormap is employed to ensure perceptual uniformity and robustness to color-vision deficiencies.

3.3 Jump Determinants: Macro Covariates

To relate jump occurrences to observable market conditions, a binary response model is estimated separately for each FAANG asset. The dependent variable $I_{i,t} \in \{0, 1\}$ denotes the daily jump indicator defined in Section 3.2.1. The empirical specification is given by

$$\log\left(\frac{P(I_{i,t}=1)}{1-P(I_{i,t}=1)}\right) = \\ = \gamma_0 + \gamma_1 \mathrm{VIX}_t + \gamma_2 R_t^{\mathrm{SP}} + \\ + \gamma_3 D_t^{\mathrm{COVID}} + \gamma_4 D_t^{\mathrm{TRADE}} + u_{i,t}, \tag{11}$$

where VIX_t denotes the daily closing level of the CBOE Volatility Index, and R_t^{SP} is the contemporaneous log return on the S&P 500, computed as the first difference of log closing prices. The indicator D_t^{COVID} equals one over March 1 – June 30, 2020, capturing the acute phase of the COVID-19 pandemic market disruption, while D_t^{TRADE} equals one over July 1 – December 31, 2018, corresponding to the escalation of the US–China trade war. The sample comprises 3,485 daily observations per asset, fully aligned with the jump indicator series.

Equation (11) is estimated via maximum likelihood. Coefficients are reported in three complementary forms to enhance interpretability: (i) log-odds estimates with associated p-values; (ii) odds ratios, computed as $\exp(\hat{\gamma}_k)$, capturing the multiplicative change in the odds of a jump for a one-unit increase in the covariate; and (iii) average marginal effects (AME), defined as

$$\mathrm{AME}_k = \frac{1}{T}\sum_{t=1}^{T} \hat{p}_{i,t}\left(1-\hat{p}_{i,t}\right)\hat{\gamma}_k, \tag{12}$$

where $\hat{p}_{i,t} = P(I_{i,t}=1 \mid X_t)$. This formulation avoids reliance on a scalar approximation and ensures consistency with the nonlinear nature of the logit model. Estimation results are reported in Tab. 6 (Section 4.3).

4 RESULTS AND DISCUSSION

4.1 Detection of Jumps and Chronological Trends

This study adopts a standardized residual approach based on Laurent et al. (2016), utilizing a GARCH (1,1) conditional volatility framework to detect jump behavior in FAANG stock returns. As illustrated in Fig. 1 and reported in Tab. 3, there is relative consistency in total jump counts across FAANG assets (42 to 48 jumps over 2012–2026), indicating that jumps are not concentrated in any single stock. However, jump distributions vary significantly from asset to asset and year to year.

In 2018, a relatively high jump count was witnessed in Google, Apple, Facebook, and Netflix stocks (5, 4, 4, 4, respectively), followed by Amazon (2), implying considerable market volatility for Google, Apple, Facebook, and Netflix. A possible reason is the heightened uncertainty about the US–China trade war and its disproportionate impact on technology sector valuations.

During the COVID-19 uncertainty period (2020), a considerable increase in jumps was witnessed across all FAANG stocks: Facebook and Amazon (5 each), and Apple, Netflix, and Google (4 each). In 2021, an obvious decline in stock jumps was observed. However, 2022

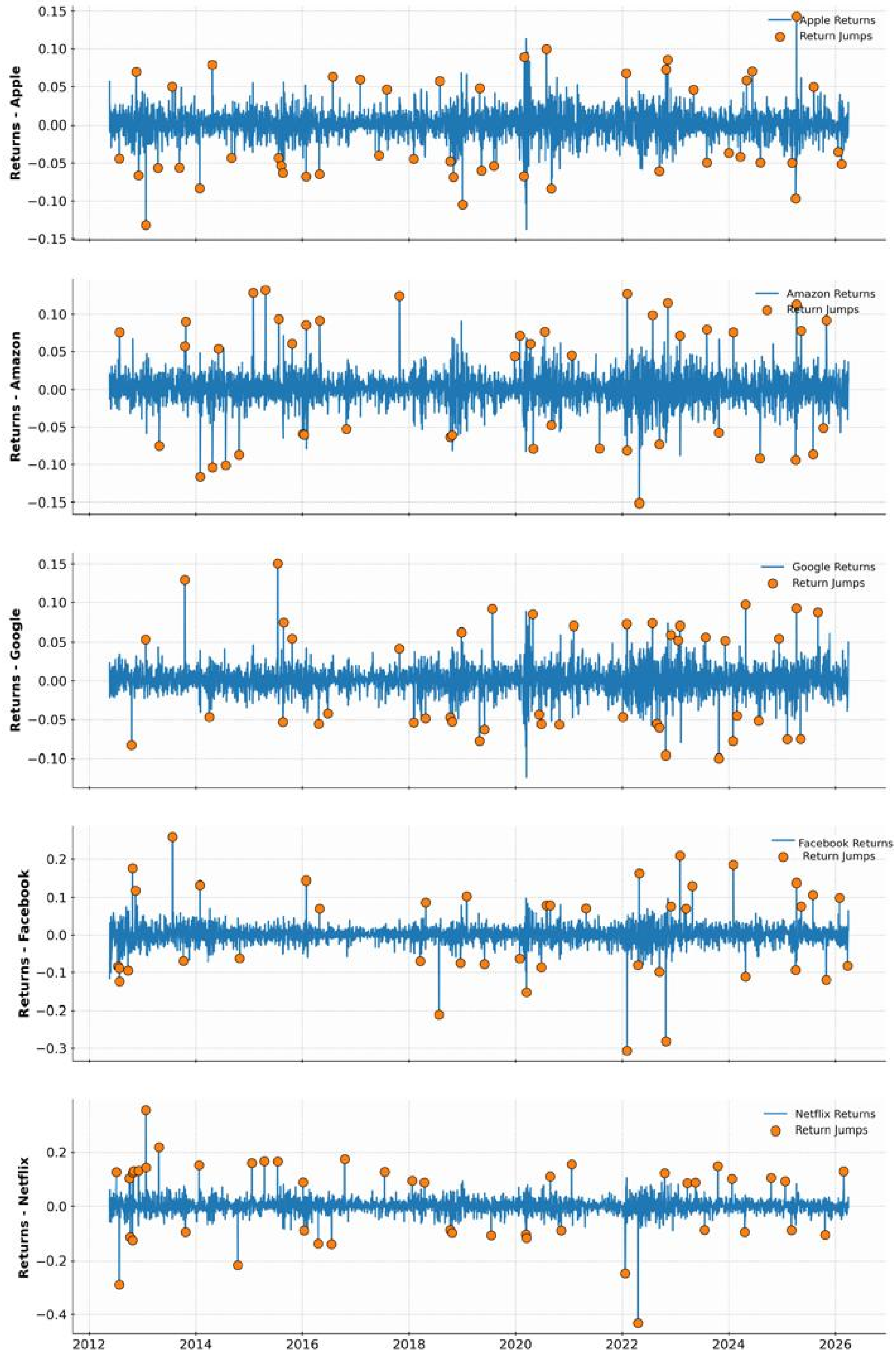

Fig. 1: Jump plots on the FAANG daily return

Tab. 3: Jump detection results by year and asset

	Panel A: Number of Jumps						Panel B: % Days with Jumps				
	Apple	Amazon	Google	Facebook	Netflix	Sum	Apple	Amazon	Google	Facebook	Netflix
2012	3	1	1	6	8	19	1.95	0.65	0.65	3.90	5.19
2013	4	3	2	2	4	15	1.59	1.19	0.79	0.79	1.59
2014	3	5	1	2	2	13	1.19	1.98	0.40	0.79	0.79
2015	3	4	4	0	3	14	1.19	1.59	1.59	0.00	1.19
2016	3	5	2	2	5	17	1.19	1.98	0.79	0.79	1.98
2017	3	1	1	0	1	6	1.20	0.40	0.40	0.00	0.40
2018	4	2	5	4	4	19	1.59	0.80	1.99	1.59	1.59
2019	4	1	3	2	1	11	1.59	0.40	1.19	0.79	0.40
2020	4	5	4	5	4	22	1.58	1.98	1.58	1.98	1.58
2021	0	2	1	1	1	5	0.00	0.79	0.40	0.40	0.40
2022	4	6	7	6	3	26	1.59	2.39	2.79	2.39	1.20
2023	2	3	5	3	4	17	0.80	1.20	2.00	1.20	1.60
2024	5	2	5	2	3	17	1.98	0.79	1.98	0.79	1.19
2025	4	6	4	5	3	22	1.60	2.40	1.60	2.00	1.20
2026	2	0	0	2	1	5	3.23	0.00	0.00	3.23	1.61
Total Jumps	48	46	45	42	47	228	1.38	1.32	1.29	1.20	1.35

Note: sample period May 18, 2012 – April 1, 2026

witnessed an increase in jumps for Google (7) and Amazon and Facebook (6 each), consistent with the impact of the Federal Reserve's aggressive rate-hike cycle on high-growth technology valuations.

These findings are broadly consistent with jump frequency estimates reported for large-cap US equities in Johnson et al. (2022), who document average annual jump rates of approximately 3–5 events for S&P 500 constituents. Our results corroborate Bouri et al. (2020) in identifying macro uncertainty as a primary driver of elevated jump activity. The network analysis extending Clements and Liao (2017), who demonstrate that high-capitalization constituents disproportionately originate index co-jumps.

4.2 Co-Jump Analysis

The logistic regression results in Tab. 4 reveal that jump activity across FAANG stocks is positively correlated on a contemporaneous basis. We emphasize that, because the logistic regression is estimated on contemporaneous jump indicators, these results capture co-movement patterns rather than causal dynamics. For instance, the Google coefficient for predicting jumps in Amazon (2.43) and the Facebook coefficient for predicting jumps in both Amazon (2.52) and Google (1.58) are statistically significant at the 1% level, indicating that days on which these assets jump are significantly more likely to also be days on which their FAANG peers jump. No significant coefficients are found for the impact of Facebook on Apple, or Netflix on Apple or Google, suggesting some independence in jump behavior for these pairs.

Applying the co-exceedance rule (Tab. 5) identifies 6 co-jump days over 2012–2026, confirming their rarity. Two occurred in 2018 (trade war period), one in 2022 (rate shock period), one in 2023, and two in April 2025 (renewed global trade policy uncertainty). This co-jump clustering around specific macro stress periods is consistent with Baruník and Fišer (2019), who show that Treasury yield curve co-jumps are predominantly driven by monetary policy announcements, and with Bouri et al. (2020), who document that cryptocurrency co-jumps

Tab. 4: Logistic regression results — co-jump associations

	Apple	**Amazon**	**Google**	**Facebook**	**Netflix**
Amazon		2.00***	2.44***	2.53***	1.42**
Apple	1.98***		1.34**		
Google	2.43***	1.34**		1.62***	
Facebook	2.52***		1.58***		1.52**
Netflix	1.29*			1.54**	

Notes: *, **, *** denote significance at 10%, 5%, 1% levels. Coefficients are log-odds. Logistic regression estimated on contemporaneous jump indicators.

coincide with elevated market-wide uncertainty and trading volume. Our result suggests the same mechanism applies to FAANG equities: co-jumps are not randomly distributed but cluster at moments of economy-wide regime shifts.

The network graph (Fig. 2 shows Amazon as the most central node, appearing in all 6 co-jump events, with the strongest pairwise linkage to Google and Facebook (9 co-jump days) and Amazon-Apple and Amazon-Netflix (7 and 4, respectively). Netflix is the most peripheral node, co-jumping with other FAANG assets on only 2 occasions, reflecting lower co-jump connectivity. These centrality patterns extend the findings of Clements and Liao (2017), who demonstrate that high-capitalization index constituents disproportionately originate co-jumps; Amazon and Google, as the two largest FAANG stocks by market cap for most of our sample, play an analogous role within the FAANG group.

4.3 Jump Determinants: Macroeconomic Analysis

Tab. 6 reports the odds ratios from the macro-covariates logistic regression (Equation 11), linking the daily jump indicator for each FAANG stock to the VIX level, the S&P 500 return, and two event dummies for the COVID-19 pandemic and the US-China trade war.

Three findings stand out. First, the VIX level is a positive and significant predictor of jump probability for four of the five FAANG stocks (Apple, Amazon, Google, Facebook), with Facebook showing the strongest sensitivity (OR $= 1.078$, $p < 0.001$). Netflix is the exception, consistent with its more idiosyncratic return profile documented in the jump network analysis (Section 4.2), where it also emerges as the most peripheral node. This VIX result reinforces the paper's central finding that FAANG jumps are not random but are tied to aggregate market conditions, consistent with the same macro environment that drives co-jump clustering.

Second, the S&P 500 return is negatively associated with jump probability for Apple and Netflix, confirming that jumps in these two stocks are concentrated on down-market days. This downside asymmetry is consistent with the negative skewness reported for all FAANG stocks in Tab. 1 and supports the interpretation that extreme price movements in FAANG stocks are predominantly losses rather than gains.

Third, neither the COVID-19 dummy nor the trade war dummy reaches statistical significance for any asset, once VIX and market returns are controlled for. This does not mean these events had no effect on jump activity, the raw jump counts in Tab. 3 clearly show elevated activity in 2018 and 2020. Rather, it confirms that the mechanism was macroeconomic: both episodes worked through elevated VIX and sharply negative market returns, channels already captured by γ_1 and γ_2. This is consistent with the co-jump analysis in Section 4.2, which identified macro stress periods as the driver of co-jump clustering rather than firm-specific factors.

Taken together, these results provide direct empirical support for the paper's core argument: FAANG jump and co-jump activity is systematically linked to observable macro conditions, with VIX serving as the primary early-

Tab. 5: The co-jumping results through Ma et al.'s (2019) approach

	Jumps-Apple	Jumps-Amazon	Jumps-Google	Jumps-Facebook	Jumps-Netflix	Number of jumps ≥ 3
10/10/2018	1	1	1	0	1	4
24/10/2018	0	1	1	0	1	3
13/9/2022	1	1	1	1	0	4
2/2/2023	0	1	1	1	0	3
3/4/2025	1	1	0	1	0	3
9/4/2025	1	1	1	1	0	4
Total number of co-jumps:						6

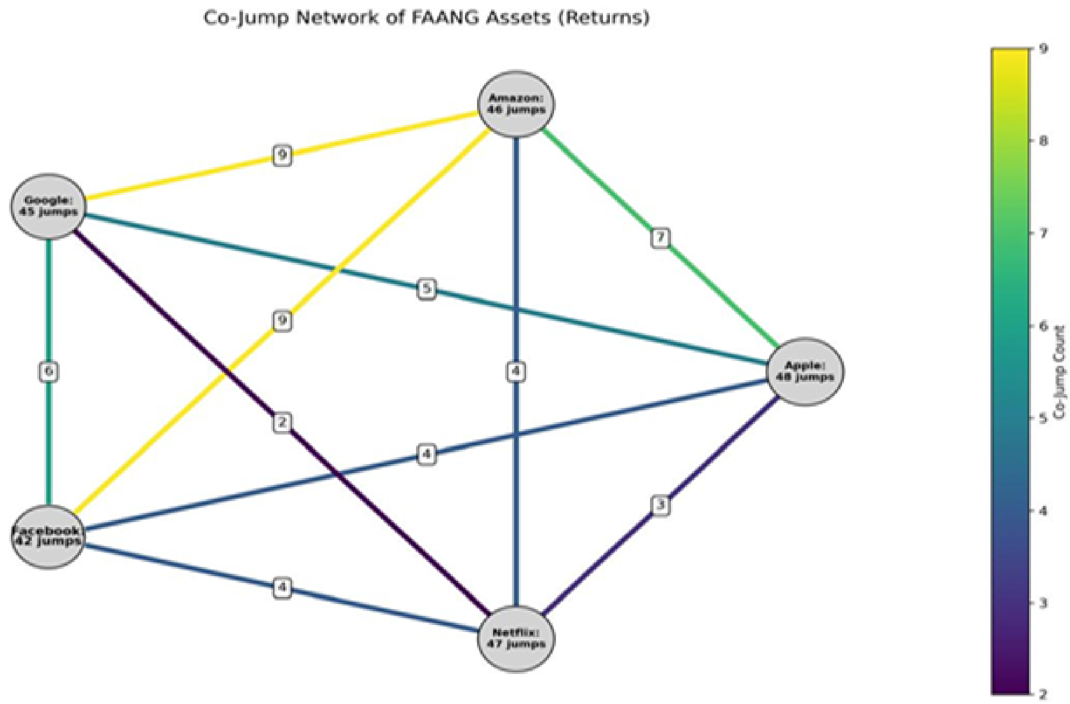

Fig. 2: The Co-Jump Network of FAANG stocks

Tab. 6: Jump Determinants – Odds Ratios [exp($\hat{\gamma}$)]

Covariate	Apple	Amazon	Google	Facebook	Netflix
VIX (level)	1.043*	1.044*	1.039*	1.078***	1.024
S&P 500 return	0.000*	0.000	0.001	2.595	0.000***
COVID dummy (2020 Q1–Q2)	0.142	0.404	0.993	0.203	0.327
Trade war dummy (2018 H2)	1.746	1.222	2.020	1.403	1.138

Notes: ***, **, * denote significance at 1%, 5%, 10%. Bold = significant. Odds ratios below 1 indicate a negative association with jump probability.

warning indicator. Portfolio managers with concentrated FAANG exposures can treat rising VIX levels as a signal for heightened jump risk, complementing the static jump-detection framework presented in Sections 3.2 and 4.1.

4.4 Systematic Patterns and Portfolio Implications

Several systematic patterns emerge from the jump and co-jump analysis, from which clear investment implications can be derived. First, jump activity is strongly counter-cyclical: the highest annual jump frequencies consistently coincide with macro stress years (2018, 2020, 2022, 2025), with 2022 recording the highest percentage of jump days across the full sample (Tab. 3, Panel B). This counter-cyclicality implies that FAANG stocks offer the least return predictability precisely when global risk appetite deteriorates.

Second, jumps in FAANG stocks are predominantly negative in direction: across all five assets, approximately 58–67% of detected jumps correspond to large negative returns (based on the sign of the standardized return Jt at jump dates). This downside asymmetry implies that jump risk in FAANG stocks is disproportionately a risk of sudden, large losses rather than gains.

Third, the six co-jump events (Tab. 5) all coincide with identifiable systemic shocks, namely the 2018 trade war technology sector sell-off, the 2022 macroeconomic rate shock, and the renewed global trade policy uncertainty in April 2025, rather than any firm-specific news. This confirms that FAANG co-jumps are macro-driven rather than idiosyncratic, meaning that within-FAANG diversification does not protect against co-jump events.

For portfolio managers, these three patterns jointly imply: (1) FAANG-only portfolios provide negligible diversification benefit during the episodes of joint extreme loss that matter most; (2) dynamic hedge strategies using VIX-linked instruments (e.g., VIX call options) may provide more reliable tail-risk protection than passive diversification; and (3) the centrality of Amazon and Google in the co-jump network suggests that these two stocks warrant higher risk-factor loadings in multi-factor risk models for FAANG portfolios.

5 CONCLUSION

This paper provides the first comprehensive analysis of jump and co-jump behavior across all five FAANG stocks over the 2012–2026 period. The FAANG group, with a combined market capitalization of approximately $9 trillion, represents the most concentrated cluster of systemically important equities in contemporary financial markets, making an understanding of their joint extreme price dynamics essential for both practitioners and regulators. Results demonstrate the presence of jump and co-jump activity within the FAANG stocks. The majority of stock jumps occur during periods of large market instability, indicating FAANG stocks' sensitivity to global shocks. Amazon emerges as the most central node in the co-jump network, appearing in all six co-jump events, with the strongest pairwise linkage to Google and Facebook (9 co-jump days), confirming Amazon's role as the primary vector of shock propagation within the FAANG cluster.

The policy and portfolio implications are direct. Because FAANG co-jumps are macro-driven (clustering around the 2018 trade war, the 2022 rate shock, and the April 2025 trade policy shock), within-FAANG diversification offers negligible protection during joint extreme loss events. Portfolio managers should consider supplementing FAANG holdings with assets that are uncorrelated with macro uncertainty (e.g., short-duration bonds, volatility strategies) and should treat Amazon as the highest-centrality risk node in any FAANG-heavy portfolio, given its participation in all six co-jump events. Policymakers monitoring systemic risk should note that co-jumps in FAANG stocks, given their dominant index weights, represent potential transmission channels from idiosyncratic technology sector shocks to broader market instability. The new macro-determinants analysis confirms that VIX is a consistent leading indicator of FAANG jump probability, suggesting that real-time volatility monitoring can serve as an early-warning system for elevated jump risk.

This study has several limitations that should inform the interpretation of results. First, we employ a standard GARCH (1,1) for conditional variance estimation rather than the BIP-GARCH of Laurent et al. (2016), which is designed to be robust to jump contamination. This may result in some upward bias in volatility estimates on jump days, potentially affecting the standardized residuals used for jump detection. Future work should implement the full BIP-GARCH specification to assess the sensitivity of jump counts to this modeling choice. Second, our analysis is based on daily data; high-frequency intraday data would allow more precise jump detection and enable the identification of intraday co-jump timing. Third, our sample of five stocks, while motivated by their systemic importance, precludes generalizations to other technology stocks or other markets.

Future studies could incorporate market sentiment, macro announcement effects, and other market measures to determine external factors that stimulate FAANG co-jumps. Decomposing jumps into positive and negative components (asymmetric jump analysis) would provide further insight into the asymmetric risk profile documented here. Extending the analysis to other technology stock clusters internationally (e.g., Chinese BAT stocks: Baidu, Alibaba, Tencent) would provide a broader perspective on whether co-jump centrality is a universal property of dominant technology firms or specific to the US market structure.

6 REFERENCES

Ali, F., Khurram, M. U. and Sensoy, A. 2025. Safe Havens for Bitcoin and Ethereum: Evidence from High-Frequency Data. *Financial Innovation*, 11, 61. DOI: 10.1186/s40854-024-00686-4.

Barndorff-Nielsen, O. E. and Shephard, N. 2006. Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. *Journal of Financial Econometrics*, 4 (1), 1–30. DOI: 10.1093/jjfinec/nbi022.

Baruník, J. and Fišer, P. 2019. Co-Jumping of Treasury Yield Curve Rates. *SSRN Electronic Journal*. DOI: 10.2139/ssrn.3382841.

Bates, D. S. 2000. Post-'87 Crash Fears in the S&P 500 Futures Options Market. *Journal of Econometrics*, 94 (1–2), 181–238. DOI: 10.1016/S0304-4076(99)00021-4.

Bonaccolto, G., Caporin, M. and Zambon, N. 2021. Multiple Co-Jumps in the Cross-Section of US Equities and the Identification of System(at)ic Movements. *The European Journal of Finance*, 27 (11), 1098–1116. DOI: 10.1080/1351847X.2020.1856704.

Bouri, E., Roubaud, D. and Shahzad, S. J. H. 2020. Do Bitcoin and Other Cryptocurrencies Jump Together? *The Quarterly Review of Economics and Finance*, 76, 396–409. DOI: 10.1016/j.qref.2019.09.003.

Clements, A. and Liao, Y. 2017. Forecasting the Variance of Stock Index Returns Using Jumps and Co-Jumps. *International Journal of Forecasting*, 33 (3), 729–742. DOI: 10.1016/j.ijforecast.2017.01.005.

de Almeida, L. A. G. 2020. Technical Indicators for Rational Investing in the Technology Companies: The Evidence of FAANG Stocks. *Jurnal Pengurusan*, 59, 75-–87. DOI: 10.17576/pengurusan-2020-59-08.

Driessen, J. and Maenhout, P. 2013. The World Price of Jump and Volatility Risk. *Journal of Banking & Finance*, 37 (2), 518–536. DOI: 10.1016/j.jbankfin.2012.09.008.

Dungey, M. and Hvozdyk, L. 2011. Co-Jumping: Evidence from the US Treasury Bond and Futures Markets. *Journal of Banking & Finance*, 35 (1), 116–129. DOI: 10.1016/j.jbankfin.2012.01.005.

Engle, R. F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50 (4), 987–1007. DOI: 10.2307/1912773.

FactSet. 2024. *FactSet Earnings Insight, Q2 2024* [online]. FactSet Research Systems. Available at: `https://www.factset.com/earningsinsight`

Johnson, J. A., Medeiros, M. C. and Paye, B. S. 2022. Jumps in Stock Prices: New Insights from Old Data. *Journal of Financial Markets*, 60, 100708. DOI: 10.1016/j.finmar.2022.100708.

LAHAYE, J., LAURENT, S. and NEELY, C. J. 2011. Jumps, Co-Jumps, and Macro Announcements. *Journal of Applied Econometrics*, 26 (6), 823–921. DOI: 10.1002/jae.1149.

LAURENT, S., LECOURT, C. and PALM, F. C. 2016. Testing for Jumps in Conditionally Gaussian ARMA–GARCH Models, a Robust Approach. *Computational Statistics & Data Analysis*, 100, 383–400. DOI: 10.1016/j.csda.2014.05.015.

MA, F., ZHANG, Y., WAHAB, M. I. M. and LAI, X. 2019. The Role of Jumps in the Agricultural Futures Market on Forecasting Stock Market Volatility: New Evidence. *Journal of Forecasting*, 38 (5), 400–414. DOI: 10.1002/for.2569.

OLIVA, I. and RENÒ, R. 2018. Optimal Portfolio Allocation with Volatility and Co-Jump Risk That Markowitz Would Like. *Journal of Economic Dynamics and Control*, 94, 242–256. DOI: 10.1016/j.jedc.2018.05.004.

PENG, W. and YAO, C. 2022. Co-Jumps, Co-Jump Tests, and Volatility Forecasting: Monte Carlo and Empirical Evidence. *Journal of Risk and Financial Management*, 15 (8), 334. DOI: 10.3390/jrfm15080334.

S&P Global Market Intelligence. 2024. *S&P 500 Sector Weights – August 2024* [online]. S&P Global. Available at: `https://www.spglobal.com/spdji/en/indices/equity/sp-500/#data`

SALEEM, K., ALHARES, O., KHAN, H. and FAROOQ, O. 2023. FAANG Stocks, Gold, and Islamic Equity: Implications for Portfolio Management During COVID-19. *Risks*, 11 (1), 19. DOI: 10.3390/risks11010019.

SEN, C. and CHAKRABARTI, G. 2023. Performance, Pandemic, and Probable Peril: Disentangling Risk, Volatility, and Bubbles in FAANG Portfolio. *New York Economic Review*, 53.

7 ANNEX

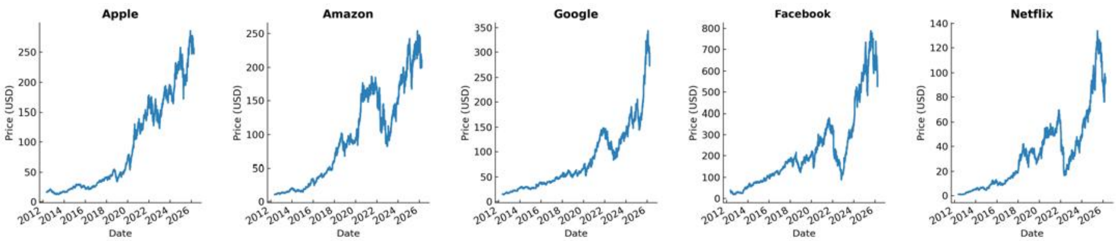

Fig. 3: Plots of price levels of FAANG stocks

Declaration of generative AI and AI-assisted technologies:

Artificial intelligence tools (OpenAI's ChatGPT, GPT-5 model) were employed to assist in refining the English language, improving sentence clarity, and suggesting structural enhancements for the manuscript. The use of AI was limited to linguistic and stylistic improvements; all core ideas, theoretical frameworks, data analyses, interpretations, and conclusions are the original work of the authors. The authors have thoroughly reviewed and validated all AI-assisted edits to ensure accuracy and academic integrity.

AUTHOR'S ADDRESS

Daouia Chebab, College of Business Administration, University of Bahrain, P.O. Box 32038, Sakhir, Kingdom of Bahrain, e-mail: dchebab@uob.edu.bh, ORCID: 0000-0001-8456-6762 (corresponding author)

Mukhriz İzraf Azman Aziz, School of Economics, Finance and Banking, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia, e-mail: mukhriz@uum.edu.my

Norzalina Ahmad, School of Economics, Finance and Banking, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia, e-mail: norzalina@uum.edu.my