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GEOPOLITICAL RISKS, MARKET VOLATILITY, AND TECH FIRMS INVOLVED IN QUANTUM COMPUTING

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Abstract. This study examines how global uncertainty influences the financial dynamics of technology firms involved in quantum computing, a strategically significant but structurally fragile segment of emerging deep-tech markets. Using daily data from January 2015 to May 2025, the analysis integrates principal component decomposition, panel regression, Granger causality testing and volatility diagnostics to assess the transmission of market volatility and geopolitical risk. The findings show that market volatility, proxied by the VIX index, exerts a persistent and adverse influence on stock returns, confirming its role as a systemic risk factor. Geopolitical risk, measured through the ACT and THREAT sub-indices of the Geopolitical Risk Index (GPR), also affects return behaviour, but through asymmetric and time-varying transmission mechanisms that emerge under heightened uncertainty and global strategic tension. The results further reveal heterogeneous vulnerability profiles across firms, indicating conditional risk spillovers rather than uniform market reactions. The study contributes new empirical evidence on the interplay between financial and geopolitical risk in advanced technology sectors and offers a replicable framework for uncertainty modelling in frontier markets.

Keywords: quantum computing, volatility, geopolitical risk, VIX, principal component analysis, clustering.

JEL Classification: D22, E32, G32, K37, M20, O16.

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1. Introduction

Quantum computing has emerged as a disruptive technological frontier with the potential to transform key sectors such as cryptography, artificial intelligence, renewable energy, and financial services (Bova et al., 2023). As technology firms advance toward commercialization, they face significant challenges related to technological immaturity, high development costs, and elevated market uncertainty (Tripathi et al., 2024). Stock market volatility in this sector is further amplified by macro-financial stressors that extend beyond firm-specific risks, intensifying concerns among investors, policymakers, and strategic stakeholders (Seskir et al., 2022).

Innovation sectors are particularly vulnerable to exogenous shocks due to their reliance on future expectations and external capital (Riel, 2022). In such environments, macroeconomic fluctuations and shifts in geopolitical sentiment can rapidly propagate through financial markets, influencing investment behaviour, funding flows, and firm valuations. These transmission mechanisms are especially relevant for companies active in quantum computing, which depend on long-term research partnerships, complex international supply chains, and cross-border collaboration (Umbrello et al., 2024). Moreover, digital technology adoption can amplify firms' sensitivity to stock price movements by increasing the informativeness of market signals, further heightening their exposure to shifts in investor sentiment and macro-financial conditions (Lan et al., 2024).

Previous literature has extensively examined the effects of market uncertainty and geopolitical risk across a wide range of innovation-oriented and technology-intensive sectors, including artificial intelligence (Urom et al., 2024), decentralized finance and blockchain technologies (Piñeiro-Chousa et al., 2022; Chowdhury et al., 2023), renewable and clean energy industries (Lucey & Ren, 2023; Liu et al., 2025), as well as financial technology and digital asset markets (Assaf et al., 2024; Yousfi & Bouzgarrou, 2024). Market volatility is typically proxied by the VIX index, the so-called "fear gauge," while geopolitical uncertainty is commonly captured by the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022), both of which have been linked to heightened financial turbulence in globally exposed sectors (Liang et al., 2023). Despite this growing body of research, firms involved in quantum computing have received limited empirical attention, even though their exposure to systemic risk is substantial due to global supply chains and reliance on long-term strategic investment. For example, Si Mohammed et al. (2023) show that geopolitical shocks during the Russia–Ukraine conflict and the post-COVID-19 period significantly altered market connectedness and hedging strategies across energy and commodity markets.

However, much of the existing literature remains sector-specific and largely descriptive, often focusing on short-term market spillovers or narrow samples of financial assets. Consequently, systematic evidence on how macroeconomic volatility and geopolitical uncertainty affect high-technology sectors, particularly quantum computing, remains limited. This shortcoming points to the need for a more integrated empirical perspective on how external risks shape financial dynamics in this strategically important field. Against this backdrop, the present study investigates the effects of market volatility, proxied by the VIX index, and geopolitical risk, captured by the GPR index and its ACT (geopolitical acts) and THREAT (geopolitical threats) components, on the stock market behaviour of leading technology firms engaged in quantum computing. Using daily data, the analysis combines principal component analysis (PCA) and clustering techniques to uncover latent structures and firm-level heterogeneity in responses to systemic uncertainty, complemented by panel regressions and Granger causality tests to examine inferential relationships and lagged effects between uncertainty measures and stock returns.

The contribution of this paper is twofold. First, it provides one of the earliest empirical assessments of the joint influence of market volatility and geopolitical risk, as measured by the VIX and GPR indices, on technology firms engaged in quantum computing, a topic that remains largely unexplored at the intersection of financial economics and emerging technologies. Second, it develops an integrated analytical framework that combines principal component analysis, K-means and hierarchical clustering with panel regressions and Granger causality tests to identify structural segmentation within the sector and capture causal direction and lagged interactions. This integrated approach reveals latent interdependencies between financial and exogenous factors and offers a clearer understanding of how systemic uncertainty affects the financial performance of firms operating in the quantum computing sector.

The findings show that companies active in the quantum computing sector are particularly sensitive to shifts in market volatility and display asymmetric responses to external uncertainty. The results point to a clear structural segmentation within the sector, with a tightly connected group of leading firms moving in line with systemic market forces and a more peripheral set of companies influenced primarily by external shocks. These dynamics highlight the importance of monitoring systemic uncertainty when assessing the financial stability of innovation-oriented industries. The study offers practical implications for investors, regulators, and policymakers aiming to strengthen resilience and design adaptive investment and innovation strategies in high-risk technological environments. By focusing on quantum-oriented technology firms, which have received limited empirical attention despite their strategic relevance, this paper extends financial risk analysis to one of the most dynamic and strategically important technological frontiers. The proposed analytical framework also provides a replicable foundation for future research on financial stability and systemic risk propagation in emerging deep-tech markets.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and identifies the main conceptual gaps. Section 3 describes the data sources and methodological framework, combining exploratory techniques (PCA and clustering) with econometric models. Section 4 presents and interprets the empirical results, while Section 5 discusses their broader theoretical and practical implications. Section 6 concludes with key policy insights, robustness considerations, and directions for future research.

2. Literature

The stock dynamics of leading technology firms involved in quantum computing are characterized by high volatility, reflecting both the emerging nature of this technological field and its sensitivity to systemic shocks such as market uncertainty and geopolitical disruptions. This behaviour can be interpreted through several established theoretical perspectives. Ambiguity and uncertainty theory, rooted in the concept of Knightian uncertainty (Epstein & Schneider, 2008), suggests that investors face inherent difficulty in evaluating payoffs when probabilities are ill-defined. Real Options Theory (Dixit & Pindyck, 1994) argues that strategic investments in high-risk, innovation-driven technologies increase exposure to external shocks by linking investment decisions to future expectations. Behavioural finance perspectives (Barberis et al., 1998) further emphasize that shifts in investor sentiment and collective biases can amplify market fluctuations. These frameworks suggest that volatility in the quantum computing sector arises from technological immaturity, reliance on external funding, evolving regulation, and heightened sensitivity to market perception.

A central variable in assessing market sentiment is the VIX index, widely regarded as a barometer of financial stress and investor uncertainty (Whaley, 2000). Empirical evidence consistently shows that increases in the VIX are associated with rising risk aversion and declining stock prices, effects that are particularly pronounced in sectors characterized by rapid innovation and growth potential (Altinkeski et al., 2024). Hoekstra and Güler (2024) further demonstrate that the influence of the VIX operates primarily through shifts in investor sentiment and trading activity, exerting stronger pressure on markets driven by technological expectations. These findings imply that companies involved in quantum computing, as part of the wider innovation intensive technology domain, are likely to exhibit amplified sensitivity to volatility shocks.

Geopolitical risk has become a critical determinant of asset price volatility and cross-market contagion. Building on the Geopolitical Risk Index, recent studies emphasize its asymmetric and sector-specific effects. For example, Pham and Hsu (2025) show that geopolitical disruptions significantly intensify volatility in the cleantech metal industry, highlighting the vulnerability of innovation-oriented sectors to global shocks. Similarly, Tiwari and Si Mohammed (2025) demonstrate that geopolitical tensions such as the Russia–Ukraine conflict alter the dynamics of fintech and green finance markets, using advanced econometric tools to capture nonlinear dependence. This body of evidence suggests that firms involved in quantum computing, given their globalized operations and reliance on strategic investment, are likely to exhibit heterogeneous and regime-dependent responses to geopolitical risk, an issue that has yet to be empirically explored.

Several studies examine quantum technologies from an ecosystem and technological perspective. Umbrello et al. (2024) highlight the role of institutional networks, policy coordination, and regional initiatives in shaping quantum innovation. Recent research has also emphasized practical applications, providing evidence on the use of quantum algorithms in areas such as energy optimization (Ghaemi Asl et al., 2024) and financial forecasting and risk modelling (Dong et al., 2025). These contributions illustrate the growing relevance of quantum technologies at the intersection of technology, economics, and sustainability. However, the literature remains largely focused on innovation ecosystems and technological development, with limited attention to the financial exposure and market vulnerability of firms involved in quantum computing when facing market volatility and geopolitical shocks.

Nevertheless, significant technological and structural risks persist in the quantum computing domain. Tripathi et al. (2024) note that scalability constraints and challenges related to quantum error correction introduce long-term uncertainty into investment decisions. Ben Jabeur et al. (2024) further suggest that these factors can weaken investor confidence and constrain firm expansion. At the same time, Chatterjee et al. (2023) argue that firms may still derive strategic and economic benefits from early adoption, even in the absence of full quantum advantage. Despite these insights, empirical evidence remains limited on how such inherent technological risks interact with broader sources of uncertainty, particularly for technology firms engaged in quantum computing.

Quantum computing firms are highly responsive to news events, technological breakthroughs, and regulatory developments. Evidence from Putranto et al. (2024) and Núñez-Merino et al. (2024) indicates that companies in this field are particularly sensitive to shifts in market sentiment. Martín-Guerrero and Lamata (2022) further suggest that quantum machine learning may contribute to risk mitigation, although its practical implementation remains limited. Despite these insights, little is known about how broader market volatility and geopolitical uncertainty may amplify sentiment-driven dynamics within quantum-oriented technology firms.

Despite the growing body of research on market uncertainty and geopolitical risk, no empirical study has yet examined the combined influence of the VIX and GPR indices on the stock market dynamics of firms active in quantum computing. Given the sector's strategic importance and structural vulnerability, this gap is both timely and relevant. Accordingly, the study tests the following hypotheses:

H0: Increases in market volatility, measured by the VIX index, are associated with declines in the stock returns and higher volatility of quantum-related technology firms.

H1: Geopolitical risk, measured by ACT and THREAT, has a conditional impact on return dynamics that emerges selectively across firms and periods.

To the best of our knowledge, this is the first empirical investigation to integrate VIX, GPR sub-indices, panel econometric analysis, Granger causality testing, and unsupervised learning techniques within a unified framework. The study thus contributes to bridging financial econometrics with strategic technology research, providing new insights into the systemic behaviour of firms operating in the quantum computing domain.

3. Data and methodology

To examine the relationship between market volatility, geopolitical risk, and the stock market dynamics of technology firms engaged in quantum computing, this study adopts an exploratory methodological framework based on advanced data analysis techniques. The primary aim is diagnostic, and the framework combines principal component analysis and clustering to identify structural patterns, complemented by panel regressions and Granger causality tests to assess inferential relationships and lagged effects. This design responds to calls for more robust empirical strategies in the analysis of systemic risk in innovation-driven sectors.

The approach contributes to financial econometrics by offering a replicable framework for analysing how macro-financial stress propagates to frontier technologies. The data structure and variable transformations are designed to be extensible to other high-technology domains, including artificial intelligence and renewable energy, thereby enhancing the comparative relevance of the framework.

3.1. Dataset

The empirical analysis uses daily data covering the period from January 2015 to May 2025. Market volatility is measured by the VIX index, while geopolitical risk is captured by two GPR sub-components, ACT and THREAT. Stock return data are collected for major technology firms involved in quantum computing, selected based on market capitalization rankings as of January 22, 2025, using information from CompaniesMarketCap (n.d.). These large-cap firms actively pursue quantum initiatives, ensuring that the sample captures companies most likely to transmit macroeconomic and geopolitical shocks within the sector. A detailed description of all variables, including company codes, data sources, and units of measurement, is provided in Table A1.

All financial data were obtained from Bloomberg (n.d.) and Investing (n.d.) to ensure accuracy and consistency. The VIX and GPR time series were collected from official and verified sources, preserving methodological reliability. The complete dataset used in this analysis is openly accessible via Zenodo: https://doi.org/10.5281/zenodo.15458994.

The observation period begins in 2015, reflecting the strategic evolution of the quantum computing field. Coccia and Roshani (2025) identify this year as a transition from an early development phase to a more mature stage characterized by industrial application and commercialization. The sample ends in May 2025, allowing for an updated assessment of systemic exposure that includes major events such as the COVID-19 pandemic, the Russia–Ukraine conflict, the 2023 banking turmoil, renewed geopolitical tensions in the Middle East, persistent inflation and monetary tightening cycles, and recent corrections in technology markets linked to the AI boom and U.S.–China strategic competition.

The financial performance of quantum computing firms is measured using daily logarithmic returns, computed as the natural logarithm of price ratios:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where P_t denotes the closing price at time t. This transformation stabilizes the variance and ensures comparability across firms with different price scales. All return series were standardized prior to analysis to facilitate meaningful comparison and dimensionality reduction through PCA.

3.2. Methodology

The methodological framework integrates exploratory and econometric components. The exploratory dimension includes correlation analysis, principal component analysis, and clustering techniques, which are used to identify co-movements, latent structures, and segmentation patterns among firms under conditions of uncertainty.

3.2.1. Correlation matrix

As a preliminary diagnostic step, the correlation matrix is used to evaluate the linear relationships among the main variables in the study. This provides an initial overview of potential co-movements between VIX, the GPR sub-indices (ACT and THREAT), and firm-level return series. By examining both the strength and direction of these correlations, the analysis helps identify early signs of multicollinearity and clustering tendencies that could influence subsequent estimations.

This step does not represent an independent analytical outcome but serves as a diagnostic foundation for the subsequent methods. In this way, the correlation matrix ensures that the empirical strategy is based on a transparent understanding of the interdependencies among variables.

3.2.2. Principal component and clustering analysis

To reduce data dimensionality and uncover latent structures, the study applies principal component analysis followed by clustering techniques. PCA condenses the main sources of variance and provides a compact representation of the relationships between the VIX index, the GPR sub-indices (ACT and THREAT), and firm-level return series, consistent with recent applications in uncertainty analysis (Luo et al., 2024). All variables are standardized prior to analysis to ensure comparability across scales. The first two principal components, selected based on the explained variance ratio, are retained for interpretation and visualization, as they capture the dominant common factors driving fluctuations across firms and uncertainty indicators.

Clustering analysis is then used to identify statistically homogeneous groups of firms according to their sensitivity to market volatility and geopolitical risk. K-means clustering is applied to the reduced feature space defined by the first two principal components, with the optimal number of clusters determined using the Elbow Method and validated through the Silhouette Score (Parnes & Gormus, 2024; Shahroodi et al., 2024). To complement these results, hierarchical clustering based on Ward's linkage is also employed to capture nested relationships within the data.

3.2.3. Panel regressions

To examine the systematic impact of market volatility and geopolitical risk on firm-level stock market dynamics, this study employs panel regression models. The panel framework is particularly suitable for this analysis as it combines the cross-sectional heterogeneity of firms with the temporal dimension of daily returns, thereby improving estimation efficiency and controlling for unobserved firm-specific effects (Hsiao, 2014).

The baseline specification can be expressed as:

$$R_{i,t} = \alpha_i + \beta_1 \cdot VIX_t + \beta_2 \cdot GPR_t + \beta_3 \cdot ACT_t + \beta_4 \cdot THREAT_t + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ denotes the daily log-return of firm i at time t, VIX_t is the market volatility index, and GPR_t together with its sub-indices ACT_t and $THREAT_t$ capture geopolitical uncertainty. Firm-specific intercepts α_i account for time-invariant heterogeneity across firms.

To capture potential regime-dependent effects, the panel regressions are estimated for both the full sample period (2015–2025) and a set of economically relevant sub-periods reflecting major shifts in global uncertainty. These include the pre-pandemic phase, the COVID-19 crisis, the period marked by the Russia–Ukraine conflict and post-pandemic market adjustment, and the most recent phase of intensified financial and geopolitical turbulence. This temporal decomposition enables an assessment of whether the sensitivity of quantum-oriented technology firms to shocks in market volatility (VIX) and geopolitical risk (GPR) varies across distinct crisis regimes and structural market conditions.

3.2.4. Granger causality

Granger causality tests are conducted within a bivariate vector autoregressive (VAR) framework, where firm-level returns $R_{i,t}$ and uncertainty measures U_t (VIX, GPR, ACT, THREAT) are modelled as:

$$R_{i,t} = \alpha_0 + \sum_{k=1}^{p} \alpha_k \cdot R_{i,t-k} + \sum_{k=1}^{p} \beta_k \cdot U_{t-K} + \varepsilon_{i,t}; \tag{3}$$

$$U_t = \gamma_0 + \sum_{k=1}^{p} \gamma_k \cdot U_{t-k} + \sum_{k=1}^{p} \delta_k \cdot R_{i,t-k} + \eta_t, \tag{4}$$

where p denotes the selected lag order. Variable U_t is said to Granger-cause $R_{i,t}$ if the null hypothesis $\beta_k = 0$ for all k is rejected, indicating that past values of uncertainty indices improve the prediction of firm returns. Conversely, $R_{i,t}$ Granger-causes U_t if the null hypothesis $\delta_k = 0$ is rejected.

3.2.5. Robustness test

To assess the stability and reliability of the empirical findings, several robustness checks are conducted to verify consistency across alternative model specifications, data transformations, and sub-sample periods.

First, principal component analysis is applied to the standardized firm-level return series to extract the first principal component (PC1), which captures the dominant co-movement among the twenty firms. PC1 is used as an aggregate market factor and serves as the dependent variable in robustness estimations.

Second, a Vector Autoregressive (VAR) model is estimated for the system comprising PC1, VIX, ACT, and THREAT. The optimal lag length is selected using the Akaike Information Criterion, while residual stationarity and model adequacy are assessed using the Phillips–Perron and Kwiatkowski–Phillips–Schmidt–Shin tests. Granger causality tests are then employed to examine predictive relationships between uncertainty measures and PC1. In addition, firm-level panel Granger causality tests are estimated for each company to confirm the persistence of causal linkages at the micro level.

Third, volatility clustering and uncertainty spillovers are examined using GARCH(1,1) models with exogenous variables (GARCH-X), where *VIX*, *ACT*, and *THREAT* enter the conditional variance equation as external shock transmitters:

$$R_t = \mu + \beta_1 \cdot VIX_t + \beta_2 \cdot ACT_t + \beta_3 \cdot THREAT_t + \varepsilon_t;$$
$$\sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2, \quad (5)$$

where R_t is the return of PC1 and σ_t^2 the conditional variance. The model was re-estimated over three sub-periods: 2015–2019, 2020–2021, and 2022–2025, to examine parameter stability under distinct market conditions.

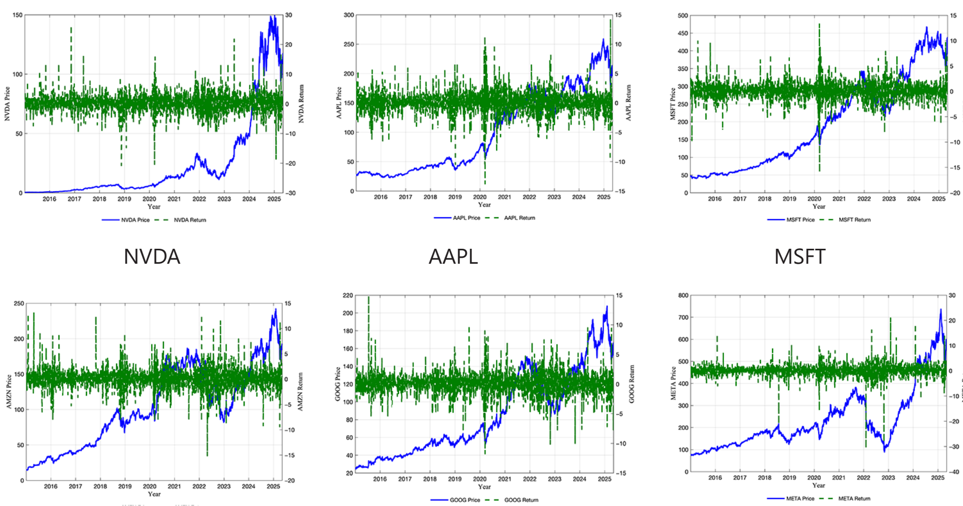
Variance Inflation Factors (VIFs) are computed for all explanatory variables to test for multicollinearity. All VIF values are close to unity, indicating a low degree of collinearity. These robustness checks confirm the stability and internal coherence of the empirical relationships between market volatility, geopolitical risk, and aggregate firm-level dynamics across alternative specifications and time horizons.

4. Results

4.1. Descriptive statistics

Figure 1 provides a visual overview of stock price and return dynamics in the sample. Descriptive statistics reported in Table A2 indicate pronounced deviations from normality across all firm-level return series, as confirmed by the rejection of the Jarque–Bera test at the 1% level. Several firms exhibit substantial fat tails, reflected in high kurtosis values, particularly NFLX, META, and SAPG, indicating exposure to extreme return events during the sample period.

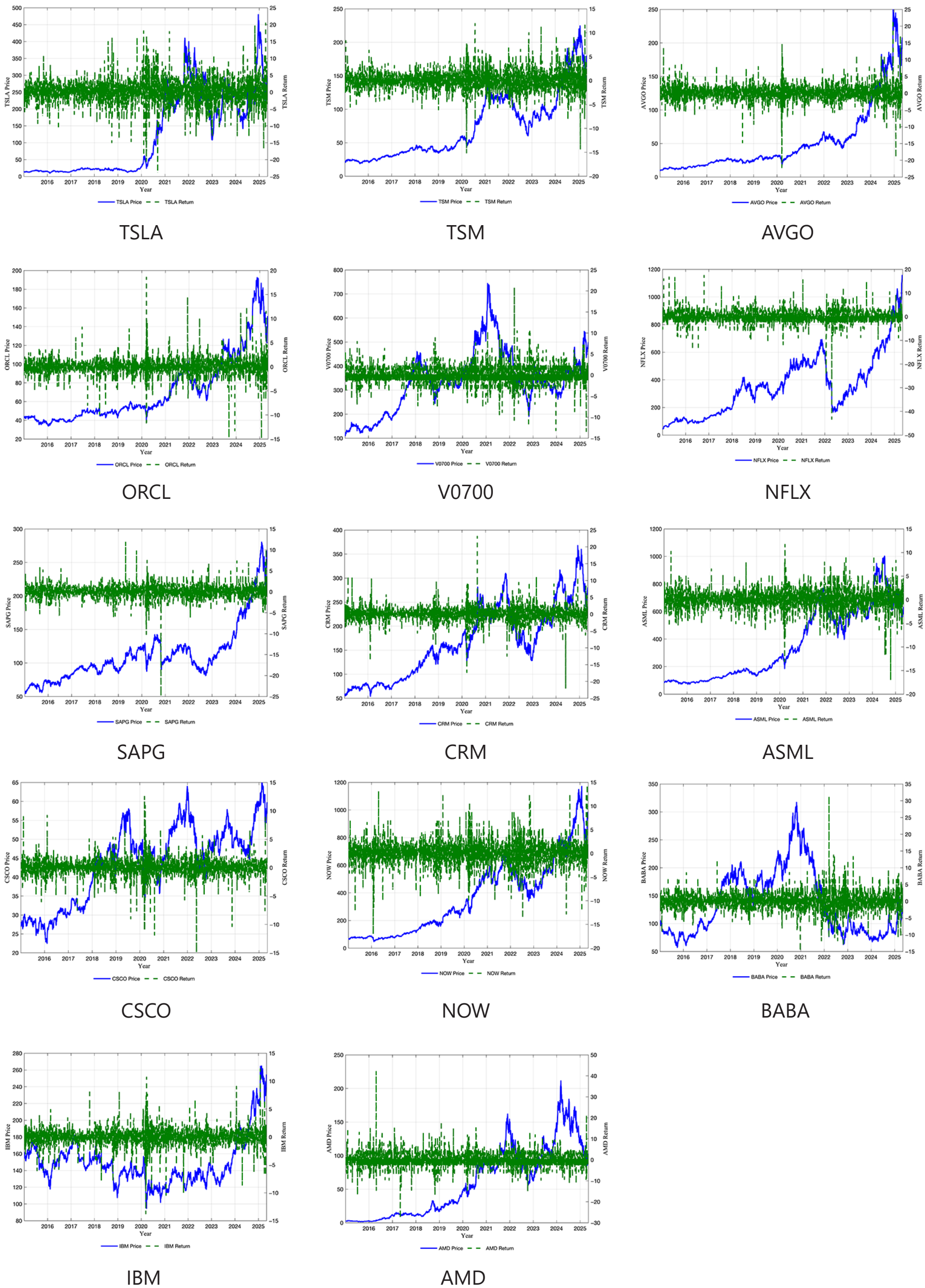
Return distributions also display marked asymmetry. BABA and AMD show positive skewness, suggesting a higher likelihood of large gains, whereas META and NFLX exhibit negative



NVDA AAPL MSFT

AMZN GOOG META

Figure 1. *To be continued*



Note: The figure illustrates the historical stock prices (blue line) and daily returns (green line) for 20 leading technology companies over the specified period.

Figure 1. Time series plots for individual companies

skewness, indicating greater vulnerability to sharp price declines. Volatility differs considerably across firms, with the highest standard deviations observed for TSLA, AMD, and NVDA, consistent with speculative trading patterns typical of high-growth technology stocks. By contrast, firms such as IBM and CSCO display lower volatility, reflecting more stable price behaviour.

Time-series properties are assessed using Augmented Dickey–Fuller, Phillips–Perron, and Kwiatkowski–Phillips–Schmidt–Shin unit root tests. All return series are stationary in levels at the 1% significance level, confirming their I(0) nature.

4.2. Correlation analysis

The correlation matrix presented in Figure 2 highlights distinct relationships between market volatility, geopolitical uncertainty, and the stock returns of technology firms engaged in quantum computing. The VIX index exhibits predominantly negative correlations with firm returns, confirming its role as a proxy for market fear and indicating that higher volatility is generally associated with weaker stock performance.

By contrast, the ACT and THREAT sub-indices show weak or near-zero linear correlations with firm-level returns, suggesting that geopolitical tensions do not generate immediate price reactions. Instead, these risks act as exogenous sources of disturbance whose effects are transmitted indirectly or with lags. Strong positive co-movements are observed among leading firms such as NVDA, AAPL, MSFT, and AMZN, reflecting shared exposure to innovation cycles, digital infrastructure investment, and macro-financial conditions. This synchronicity points to a tightly integrated core within the technology sector.

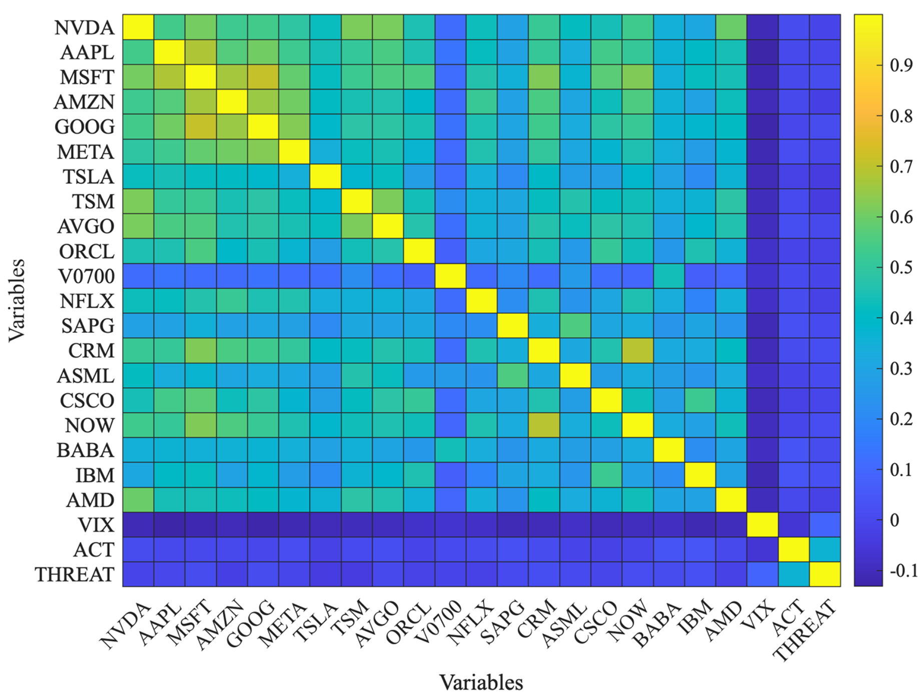


Figure 2. Correlation matrix

Although the direct linear correlation between VIX and GPR is modest, both indicators display concurrent peaks during major crisis episodes, reinforcing perceptions of systemic instability. Prior evidence shows that the impact of geopolitical risk intensifies during periods of conflict escalation and is often transmitted through nonlinear and regime-dependent channels (Khan et al., 2024; Liang et al., 2023; Zhang & Wu, 2024).

The results suggest a dual structure within the quantum computing sector, characterized by strong firm-level co-movement driven by market cycles and more peripheral effects from volatility and geopolitical risk. These findings motivate the use of dimensionality-reduction techniques and causality tests in the subsequent analysis to uncover dynamic interactions beyond linear correlations.

4.3. Event-driven firm dynamics

Stock market trajectories of technology firms engaged in quantum computing during 2015–2025 were shaped by a sequence of global shocks, each generating distinct patterns of volatility and recovery. During the US–China trade tensions of 2018–2019, firms with strong exposure to Asian supply chains, including BABA, TSM, and V0700, experienced sharper declines, reflecting the amplifying role of trade-related uncertainty on financial risk. This pattern is consistent with evidence from Chen et al. (2026), who document persistent investment distortions across high-technology industries during the trade war.

The COVID-19 crisis of 2020–2021 produced the most abrupt market disruption, with sharp corrections across all firms in early 2020. The subsequent recovery revealed pronounced heterogeneity, as companies such as MSFT, AMZN, NVDA, and AAPL rebounded rapidly, supported by demand for cloud services and semiconductors, while META, NFLX, and TSLA remained highly volatile.

The Russia–Ukraine conflict and the tightening of global monetary conditions during 2022–2023 renewed downward pressures on equity markets. NVDA and MSFT showed relative resilience, driven by capital inflows linked to AI-related investment cycles, whereas TSLA and META responded more strongly to geopolitical shocks, consistent with asymmetric spillover effects documented by Alnafisah et al. (2025).

The period from 2023 to 2025 was characterized by heightened financial turbulence associated with events such as the collapse of Silicon Valley Bank, renewed US–China tensions, and escalating conflicts in the Middle East. These developments intensified market uncertainty and widened divergence in firm responses, with more stable firms such as IBM and CSCO remaining relatively insulated, while more speculative firms, including TSLA and AMD, experienced amplified fluctuations, in line with contagion dynamics observed during financial stress episodes (Pandey et al., 2023; Ali et al., 2023).

4.4. Principal component analysis

To identify the dominant sources of variation among technology firms engaged in quantum computing, PCA was applied to the standardized stock return series together with the uncertainty indicators. The scree plot in Figure 3 shows that the first five principal components explain close to 70% of the total variance, which indicates that a reduced number of latent factors capture most of the co-movement in the dataset.

The loading patterns of the first two components reveal that firm-level return variables, particularly those associated with NVDA, AAPL, and MSFT, contribute most strongly to the dominant components. This suggests that a small group of highly capitalized firms drives the aggregate dynamics of the sector and exerts systemic influence over market behaviour. In contrast, the geopolitical risk sub-indices ACT and THREAT are positioned at the margins of the component space, confirming their weak integration with firm-level financial variability and supporting their interpretation as external sources of uncertainty. The VIX index lies between these two groups, which indicates that market volatility is partially embedded in the return structure of the firms but does not dominate it.

PCA reveals a distinction between the internal coherence of the sector, reflected in the strong joint movement of firm returns, and the role of external uncertainty variables, which influence the system from outside the core return structure. The reduced representation obtained through PCA provides a meaningful synthesis of the data and a suitable basis for the clustering analysis presented in the following subsection.

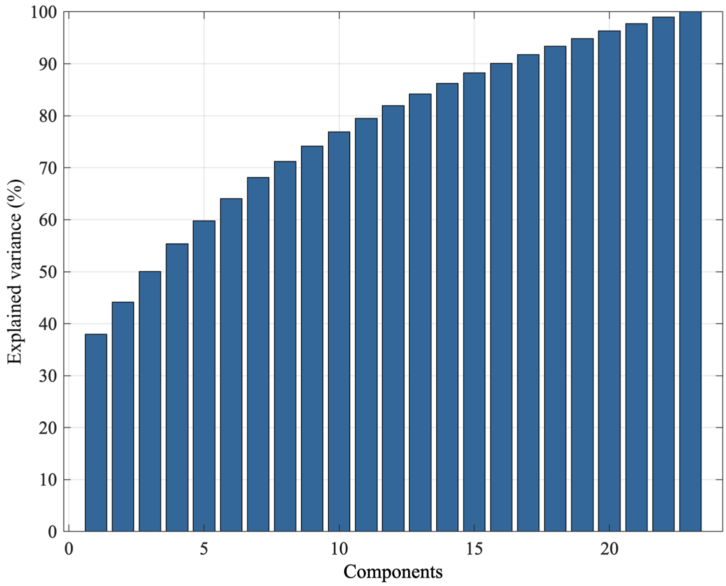


Figure 3. Scree plot showing cumulative variance explained by principal components

4.5. Clustering analysis

To complement the PCA results and examine structural segmentation within the dataset, clustering techniques are employed to identify groups of firms exhibiting similar behaviour under market volatility and geopolitical risk. As shown in Figure 4, a clear inflection at $k = 3$ indicates that a three-cluster solution offers the most appropriate balance between model simplicity and explanatory power.

The robustness of the clustering structure is further evaluated using the Silhouette Score, which measures cluster cohesion and separation. As illustrated in Figure 5, the score peaks at $k = 2$ but remains relatively stable at $k = 3$, supporting the interpretability of the three-cluster solution and justifying its use in the subsequent analysis.

The K-means clustering shown in Figure 6 confirms a segmented structure within the dataset. Cluster 1 comprises the majority of technology firms, which exhibit strong co-movement and high integration.

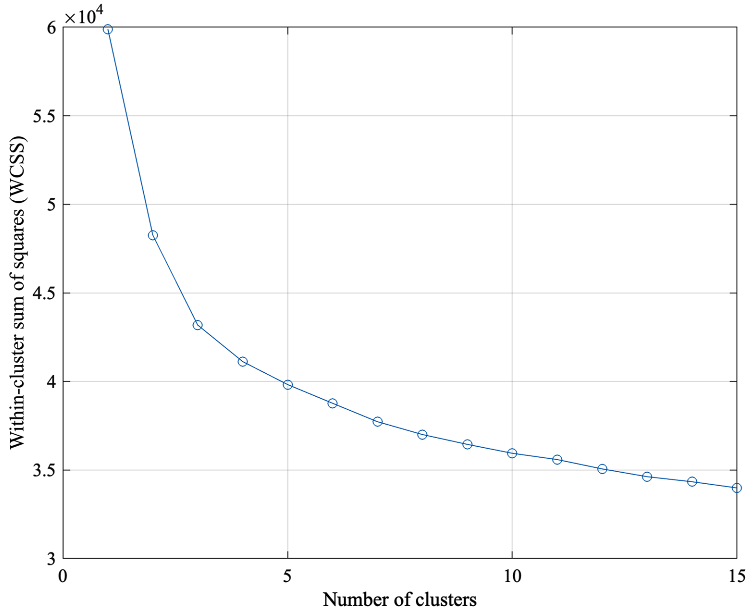


Figure 4. Elbow curve for optimal cluster selection

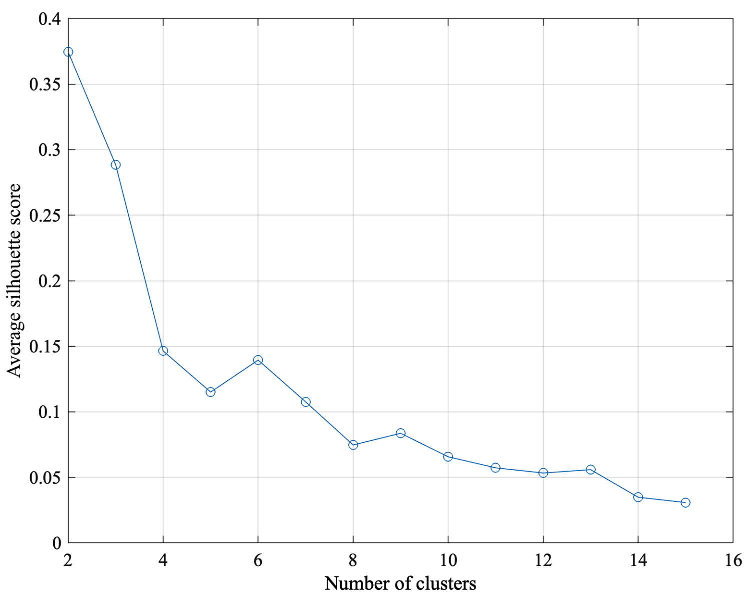


Figure 5. Silhouette analysis for cluster validation

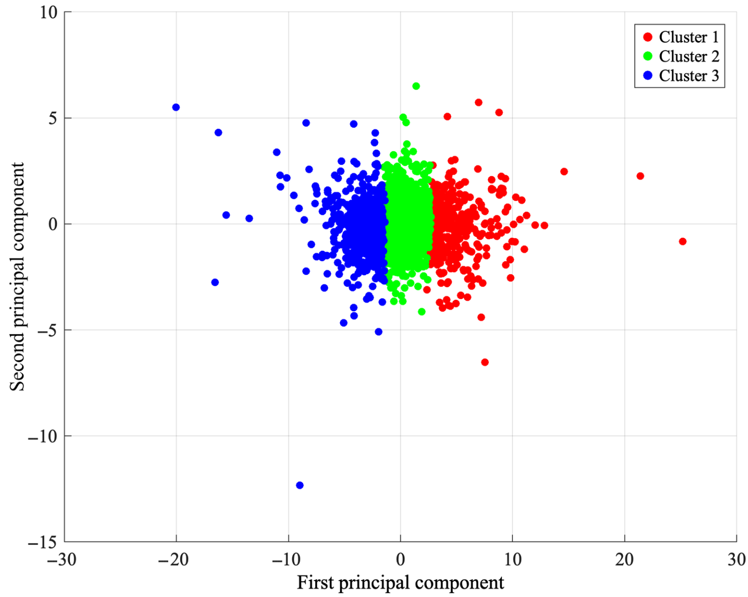


Figure 6. K-means clustering on the first two principal components

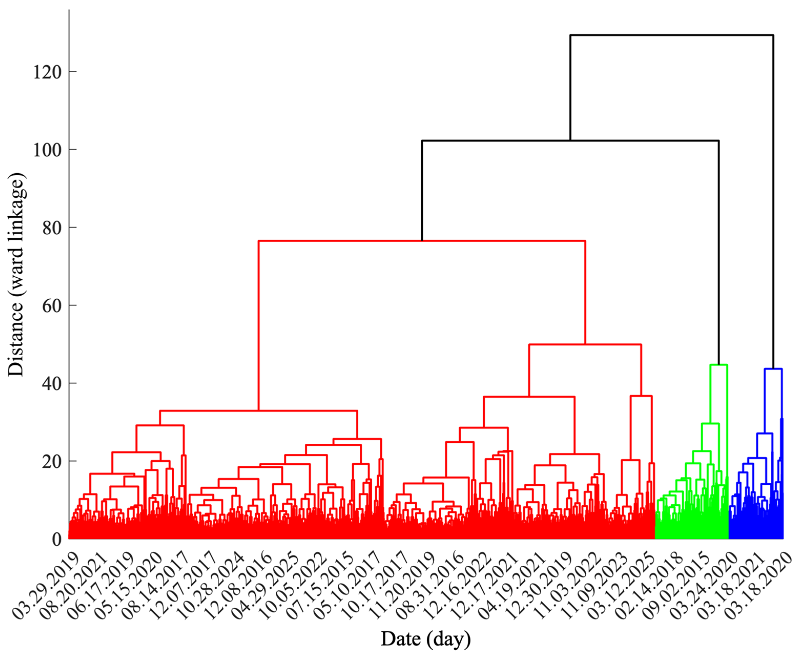


Figure 7. Hierarchical clustering dendrogram based on Ward's linkage

Cluster 2 consists solely of the VIX index, whose intermediate position indicates that market-wide volatility is partially linked to firm dynamics but remains externally driven. Cluster 3 includes the ACT and THREAT components of geopolitical risk, which are clearly separated from firm-level variables, consistent with their role as exogenous and episodic sources of uncertainty.

Hierarchical clustering, presented in Figure 7 using a dendrogram based on Ward's linkage, reinforces these findings by capturing temporal regimes over the 2015–2025 period. The resulting branches align with major episodes of global turbulence, indicating that shifts in market regimes are primarily driven by crisis episodes rather than structural changes in firm-level co-movement.

Both clustering approaches consistently identify three meaningful groupings within the dataset. The first corresponds to a systemic core composed of quantum-related firms such as NVDA, AAPL, MSFT, and AMZN, which display strong co-movement and similar exposure to macro-financial conditions. The second group is represented by the VIX index, which occupies an intermediate position and captures market-wide volatility spillovers. The third grouping consists of the ACT and THREAT geopolitical risk indicators, which remain structurally detached from firm-level behaviour and operate as exogenous sources of uncertainty.

4.6. Panel regressions and Granger causality

Panel regression results point to the dominant role of market-wide volatility in shaping return dynamics among technology firms engaged in quantum-related activities. Across all model specifications, the VIX coefficient is negative and statistically significant, confirming its function as a systemic risk proxy that exerts downward pressure on stock performance during periods of heightened financial stress. By contrast, the geopolitical risk indicators ACT and THREAT display weaker and less stable effects, reaching statistical significance only under specific conditions. This pattern indicates that geopolitical tensions affect firm-level returns selectively rather than uniformly.

Panel stationarity is confirmed using Levin–Lin–Chu, Im–Pesaran–Shin, and Fisher-type ADF and PP tests, supporting the suitability of the panel structure for inference (Table A3).

Granger causality analysis complements the regression results by examining predictive relationships. At the aggregate level, where the first principal component (PC1) proxies the common market factor (Table 1), only VIX Granger-causes PC1, while ACT and THREAT remain insignificant. This finding reinforces the pervasive impact of volatility shocks across firms, whereas geopolitical risk does not generate uniform market reactions.

At the firm level, panel Granger causality results (Table A4) indicate that VIX Granger-causes returns for 16 of the 19 firms, highlighting strong volatility spillover effects. In contrast, ACT shows predictive power for only a limited subset of companies, including NVIDIA and Apple, while THREAT primarily affects internationally exposed firms such as TSM, BABA, and IBM. These heterogeneous responses reflect differences in geopolitical exposure related to supply chain structure, market positioning, and strategic dependence. The full pairwise Granger causality matrix is provided in the Zenodo supplementary repository due to space constraints.

The findings provide strong empirical support for H_0, confirming the systemic and persistent influence of market volatility on return behaviour. H_1 is also supported, as geopolitical risk influences return dynamics through asymmetric and conditional transmission mechanisms that emerge under specific market regimes.

Table 1. Granger causality results for the first principal component (PC1)

Cause PC1	Reject H_0	*p*-value
VIX	1	0.000
ACT	0	0.067
THREAT	0	0.074

Note: The null hypothesis (H_0) states that the variable does not Granger-cause PC1.

4.7. Robustness checks

Several robustness checks are conducted to assess the reliability of the empirical findings. First, the stationarity of the return series is re-examined using Augmented Dickey–Fuller tests with structural breaks to account for potential regime shifts in financial time series (Table A5). The identified breakpoints align with major market disruptions, including the 2015–2016 global slowdown, the COVID-19 liquidity crisis, the onset of the Russia–Ukraine conflict in 2022, and renewed uncertainty during 2023–2024. All series remain stationary at the 1% significance level after allowing for structural breaks, indicating that the results are not driven by non-stationarity.

Second, regime dependence is evaluated through sub-period estimation of GARCH(1,1) models (Table A6). Although volatility persistence increases after 2022, the dominant role of the VIX index as a source of systemic transmission remains stable across all sub-periods, while the effects of ACT and THREAT continue to appear conditional and episodic. This confirms that the main findings are robust to alternative time windows.

Finally, the robustness of the causality structure is assessed by comparing panel Granger causality results with the full pairwise Granger causality matrix available in the Zenodo repository. The strong consistency between firm-level and pairwise outcomes indicates that the identified dependency patterns are not artefacts of model specification or sample composition. These diagnostics support the validity of the econometric framework and the empirical conclusions.

5. Discussions

The findings point to an asymmetric pattern of risk transmission in the quantum technology sector, in which financial fragility is shaped primarily by market-wide volatility rather than by geopolitical uncertainty. The dominant role of the VIX index, reflected in its consistently negative coefficients in panel regressions and its Granger-causal influence for 16 of the 19 firms, highlights the central importance of investor sentiment and global risk aversion in driving stock price dynamics. This result aligns with Coccia et al. (2022), who argues that emerging high-technology sectors are structurally sensitive to external disturbances due to speculative capital flows and technological immaturity.

By contrast, the geopolitical risk indicators ACT and THREAT exhibit weaker and episodic effects. This pattern is consistent with Caldara and Iacoviello (2022), who emphasize that geopolitical shocks typically operate through indirect macro-financial channels rather than exerting uniform firm-level effects. Within the quantum computing sector, the limited direct impact of geopolitical risk may reflect forward-looking investor behaviour that prioritizes long-term technological prospects over short-term political events. At the same time, geopolitical risk becomes relevant for firms with strong exposure to global semiconductor supply chains, such as TSM, BABA, and IBM, indicating selective transmission through trade dependencies, export controls, and technological security considerations.

These insights are reinforced by the principal component analysis, which reveals periods of collective movement during market stress alongside persistent heterogeneity in firm-level risk sensitivity. This evidence is consistent with Prasad (2023) and Martín-Guerrero and Lamata (2022), who note that quantum technology firms differ substantially in technological maturity and commercialization trajectories. The observed dynamics suggest that uncertainty in the sector is regime-dependent rather than uniform.

The results indicate that macro-financial volatility exerts a persistent and systemic influence on quantum-related firms, while geopolitical risk operates as a secondary factor that becomes salient under conditions of heightened uncertainty. Similar patterns have been documented in other innovation-driven sectors, including renewable energy (Chen et al., 2024) and fintech markets (Yousfi & Bouzgarrou, 2024), where risk transmission occurs through indirect and nonlinear mechanisms. The analysis also highlights the value of combining econometric techniques with unsupervised learning methods to uncover latent structures in risk transmission that may remain undetected using conventional empirical approaches.

6. Conclusions and policy implications

This study examines the role of market volatility, measured by the VIX index, and geopolitical uncertainty, captured by the GPR index, in shaping stock return dynamics within advanced technology sectors. Although simple correlations suggest weak direct links between macro-risk indicators and returns, the econometric analysis reveals a deeper structural vulnerability. Firms operating in innovation-intensive industries display heightened sensitivity to external shocks due to their reliance on speculative capital inflows, globalized supply chains, and policy stability. This fragility distinguishes the sector from adjacent innovation domains such as artificial intelligence or blockchain.

The empirical results support H0, confirming that market volatility acts as a systemic risk factor with a persistent and adverse effect on return behaviour. H1 is also supported, as geopolitical risk, proxied by the ACT and THREAT sub-indices, influences returns through asymmetric and regime-dependent transmission mechanisms. Although geopolitical shocks do not affect firms uniformly, their economic relevance increases under elevated uncertainty, particularly for companies exposed to international supply chain disruptions and technology security constraints. These findings contribute to the literature by showing that uncertainty propagates through conditional and nonlinear channels rather than through uniform market responses.

The results carry important implications for financial stability monitoring and risk management. Asset markets respond not only to macroeconomic volatility but also to strategic disruptions in technology supply chains and geopolitical competition. Early-warning frameworks should therefore integrate sentiment-based indicators such as VIX and GPR with technology-specific signals, including patent activity, export controls, and semiconductor policy developments. Policy interventions should move beyond short-term financial stabilization and focus on strengthening long-term resilience through targeted R&D support, cross-border standard-setting in quantum and semiconductor technologies, and coordinated risk mitigation mechanisms.

Several limitations warrant consideration. The analysis relies on linear specifications and does not account for firm-level fundamentals such as leverage, R&D efficiency, or ownership structure. Future research could adopt nonlinear and high-dimensional approaches, including regime-switching models, tail-risk spillover analysis, and network-based contagion frameworks, to better capture structural breaks and shifts in geopolitical regimes. All supplementary materials, including firm-level causality matrices and replication codes, are available through the Zenodo repository, supporting transparency and reproducibility.

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APPENDIX

Table A1. Description of the variables

Category	Variable (code)	Market/region	Unit
Dependent variables	NVIDIA Corporation (NVDA)	United States (NASDAQ)	Closing price (USD/unit)
	Apple Inc (AAPL)	United States (NASDAQ)	Closing price (USD/unit)
	Microsoft Corporation (MSFT)	United States (NASDAQ)	Closing price (USD/unit)
	Amazon. Com Inc (AMZN)	United States (NASDAQ)	Closing price (USD/unit)
	Alphabet Inc Class C (GOOG)	United States (NASDAQ)	Closing price (USD/unit)
	Meta Platforms Inc (META)	United States (NASDAQ)	Closing price (USD/unit)
	Tesla Inc (TSLA)	United States (NASDAQ)	Closing price (USD/unit)
	Taiwan Semiconductor Manufacturing (TSM)	Taiwan (TWSE)	Closing price (USD/unit)
	Broadcom Inc (AVGO)	United States (NASDAQ)	Closing price (USD/unit)
	Oracle Corporation (ORCL)	United States (NYSE)	Closing price (USD/unit)
	Tencent Holdings Ltd (V0700)	Hong Kong (HKEX)	Closing price (HKD/unit)
	Netflix Inc (NFLX)	United States (NASDAQ)	Closing price (USD/unit)
	SAP SE (SAPG)	Germany (XETRA)	Closing price (EUR/unit)
	Salesforce Inc (CRM)	United States (NYSE)	Closing price (USD/unit)
	ASML Holding NV (ASML)	Netherlands (Euronext Amsterdam)	Closing price (USD/unit)
	Cisco Systems Inc (CSCO)	United States (NASDAQ)	Closing price (USD/unit)
	ServiceNow Inc (NOW)	United States (NYSE)	Closing price (USD/unit)
	Alibaba Group Holdings Ltd ADR (BABA)	China/US ADR (NYSE)	Closing price (USD/unit)
	International Business Machines (IBM)	United States (NYSE)	Closing price (USD/unit)
	Advanced Micro Devices Inc (AMD)	United States (NASDAQ)	Closing price (USD/unit)
Inde-pendent variables	CBOE Volatility Index (VIX)	United States	Numerical value
	Geopolitical Risk (ACT)	Global	Risk index
	Geopolitical Risk (THREAT)	Global	Risk index

Table A2. Descriptive statistics

	Mean	Med.	Max.	Min.	Std. Dev.	Skew.	Kurt.	JB	IQR	Prob.
NVDA	0.209	0.122	26.373	−20.794	3.110	0.147	9.747	4 951.0	3.18	0.000
AAPL	0.076	0.084	14.262	−13.771	1.838	−0.107	9.311	4 327.7	1.76	0.000
MSFT	0.086	0.085	13.293	−15.945	1.724	−0.093	10.951	6 865.4	1.67	0.000
AMZN	0.097	0.100	13.193	−15.143	2.075	0.165	8.777	3 634.8	2.03	0.000
GOOG	0.068	0.111	14.906	−11.766	1.816	0.023	9.021	3 935.1	1.69	0.000
META	0.078	0.105	20.931	−30.639	2.404	−1.160	29.216	75 181.0	2.15	0.000
TSLA	0.115	0.109	20.449	−23.652	3.649	−0.026	7.417	2 118.4	3.59	0.000

End of Table A2

	Mean	Med.	Max.	Min.	Std. Dev.	Skew.	Kurt.	JB	IQR	Prob.
TSM	0.079	0.078	11.914	−15.122	2.075	0.029	7.510	2 208.2	2.16	0.000
AVGO	0.116	0.113	21.859	−22.186	2.438	−0.086	14.092	13 357.0	2.37	0.000
ORCL	0.046	0.085	18.587	−14.839	1.808	0.119	18.961	27 656.8	1.53	0.000
V0700	0.058	0.000	20.829	−13.393	2.208	0.239	9.410	4 484.0	2.24	0.000
NFLX	0.121	0.066	17.419	−43.258	2.774	−1.340	32.081	92 573.0	2.58	0.000
SAPG	0.058	0.056	11.822	−24.766	1.585	−1.313	30.261	81 414.2	1.54	0.000
CRM	0.059	0.090	23.147	−21.986	2.201	−0.173	16.157	18 803.2	2.00	0.000
ASML	0.075	0.108	11.700	−17.012	2.113	−0.354	7.573	2 324.0	2.21	0.000
CSCO	0.029	0.045	12.552	−14.769	1.593	−0.616	14.808	15 298.6	1.45	0.000
NOW	0.103	0.206	14.400	−17.027	2.500	−0.214	7.795	2 515.6	2.46	0.000
BABA	0.007	– 0.035	31.309	−14.320	2.629	0.710	13.636	12 498.1	2.60	0.000
IBM	0.017	0.067	12.190	−13.755	1.553	−0.473	13.563	12 207.4	1.40	0.000
AMD	0.140	0.048	42.062	−27.746	3.647	0.534	13.204	11 425.4	3.71	0.000

Note: This table presents the descriptive statistics of the analysed variables, including the mean, median, maximum and minimum values, standard deviation, skewness, and kurtosis coefficients, as well as the results of the Jarque-Bera test (JB) and the associated probability.

Table A3. Panel stationarity diagnostics for the Granger framework (LLC, IPS, Fisher-ADF/PP)

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	– 199.943	0.000	23	59876
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	–249.904	0.000	23	59876
ADF—Fisher Chi-square	720.698	0.000	23	59876
PP—Fisher Chi-square	518.589	0.000	23	59892

Note: * denotes the adjusted t-statistic reported for the Levin, Lin & Chu (LLC) test; ** Probabilities for Fisher tests are computed using an asymptotic Chisquare distribution. All other tests assume asymptotic normality.

Table A4. Firm-level panel Granger causality results between VIX, ACT, THREAT, and stock returns

Company	VIX reject	ACT reject	THREAT reject	VIXp	ACTp	THREATp
NVDA	1	1	0	0.006	0.045	0.068
AAPL	1	1	0	0.000	0.044	0.076
MSFT	1	0	0	0.000	0.200	0.061
AMZN	1	0	0	0.021	0.212	0.234
GOOG	1	0	0	0.000	0.187	0.147
META	1	0	0	0.005	0.177	0.222
TSLA	1	0	0	0.000	0.072	0.753
TSM	1	0	1	0.013	0.180	0.041

End of Table A4

Company	VIX reject	ACT reject	THREAT reject	VIXp	ACTp	THREATp
AVGO	1	0	0	0.002	0.153	0.116
ORCL	1	0	0	0.000	0.190	0.073
V0700	0	0	1	0.396	0.229	0.039
NFLX	1	0	0	0.035	0.267	0.956
SAPG	0	0	0	0.073	0.955	0.061
CRM	1	0	0	0.002	0.174	0.418
ASML	0	0	0	0.570	0.404	0.059
CSCO	1	0	1	0.000	0.434	0.029
NOW	1	0	0	0.000	0.720	0.135
BABA	0	0	1	0.262	0.087	0.005
IBM	1	0	1	0.000	0.068	0.021
AMD	1	0	0	0.002	0.180	0.543

Note: "VIX reject", "ACT reject", and "THREAT reject" indicate whether the null hypothesis of no Granger causality is rejected (1 = reject H_0, 0 = fail to reject). "VIXp", "ACTp", and "THREATp" report the corresponding *p*-values.

Table A5. ADF structural break unit root test results

Company	Break date	*t*-Statistic	Prob.
NVDA	11.11.2016	–55.61	<0.01
AAPL	03.12.2020	–54.73	<0.01
MSFT	03.12.2020	–58.96	<0.01
AMZN	01.30.2015	–52.45	<0.01
GOOG	07.17.2015	–54.51	<0.01
META	10.27.2022	–54.90	<0.01
TSLA	03.16.2020	–51.68	<0.01
TSM	07.27.2020	–56.73	<0.01
AVGO	01.08.2015	–5538	<0.01
ORCL	03.12.2020	–57.03	<0.01
V0700	12.22.2023	–50.62	<0.01
NFLX	04.20.2022	–53.59	<0.01
SAPG	10.26.2020	–55.91	<0.01
CRM	08.26.2020	–54.99	<0.01
ASML	03.18.2020	–50.76	<0.01
CSCO	05.19.2022	–57.39	<0.01
NOW	01.28.2016	–54.32	<0.01
BABA	03.16.2022	–53.04	<0.01
IBM	03.12.2020	–54.79	<0.01
AMD	04.22.2016	–54.94	<0.01

Note: This table reports the results of the Augmented Dickey–Fuller (ADF) unit root tests with structural breaks for each firm-level return series. The reported break dates indicate the most significant structural changes in the data. All series are stationary at the 1% significance level, confirming that the presence of breaks does not alter the overall stationarity of the return processes.

Table A6. GARCH(1,1) estimates across subperiods testing structural stability and volatility effects

Start	End	Nobs	ω	α	β	DoF	μ	VIX	ACT	THREAT
01.02.2015	31.12.2019	1 237.000	2.566	0.168	0.756	6.260	3.694	–0.281	0.003	0.002
01.01.2020	31.12.2021	504.000	2.573	0.218	0.744	11.870	3.001	–0.155	0.011	0.001
01.01.2022	09.05.2025	841.000	0.319	0.039	0.957	8.031	5.456	–0.260	–0.005	–0.001

Note: The table reports GARCH(1,1) estimates with Student-t distributed errors over three subperiods. Nobs denotes the number of observations used in each estimation. ω represents the constant term in the conditional variance equation, α measures the short-term reaction of volatility to shocks, and β captures volatility persistence. DoF refers to the degrees of freedom of the Student-t distribution, while μ denotes the conditional mean. VIX, ACT, and THREAT are coefficients of exogenous variables representing market volatility, economic activity, and thematic risk, respectively.