SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 5881-5892
Open Access. Online & Print

DOI: 10.5281/zenodo.19401228

WHEN WARS MEET ALGORITHMS: DO WARS AND EXTREME EVENTS ALTER THE U.S. DEFENCE AND GLOBAL AI STOCKS' CORRELATIONS?

Hela Ben Hamida[1]

[1]*College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia.*

Received: 20/02/2026
Accepted: 30/03/2026

Corresponding Author: Hela Ben Hamida
(hmbenhamida@imamu.edu.sa)

ABSTRACT

This paper explores the impact of global risk factors and extreme events on the dynamic correlations between U.S. defence stocks and global artificial intelligence stocks, employing three complementary methods: the multivariate GARCH model with standard and asymmetric dynamic conditional correlation, the GARCH-X model, and wavelet quantile correlations. The data used covers the period from November 2016 to October 2025. We uncover that the correlation between AI and U.S. defence stocks is weakly positive and exhibits a significant time-varying pattern. Oil market volatility is the most influential factor shaping the strength of this correlation. Additionally, geopolitical shocks such as the Ukrainian and Gaza wars, the COVID-19 pandemic, and trade tariff shocks have increased volatility in the correlation between AI-defence stocks. In the time-frequency domain, the influence of global risk factors appears heterogeneous and depends on market conditions. These new findings hold meaningful operational implications for portfolio managers and policymakers, especially regarding the integration of global AI technologies into the US defence industry, offering valuable insights for decision-making.

KEYWORDS: Defence stocks – AI – Correlation-GARCH-DCC/ADCC- GARCH-X- Wavelet quantile correlation.

1. INTRODUCTION

The fast growth of artificial intelligence (AI) technologies has significantly affected investment across global capital markets. Defence stocks, which have traditionally been considered safe assets tied to government budgets (Song et al., 2025), are now being redefined as innovative vehicles for next-generation systems that increasingly incorporate AI capabilities. The competition in AI has become a key focus for the US, particularly amid its strategic rivalry with Russia and China. The statistics tell a compelling story. The Stockholm International Peace Research Institute (SIPRI Report, April 2025) stated that: global defence spending reached USD 2.7 trillion in 2024, fuelled by recent geopolitical tensions, including the war in Ukraine, the Gaza-Israel conflict, and nuclear tensions between Israel and Iran" (Xiao et al., 2025, p.1). According to the Precedence Research Report (July 2025), the global AI market in aerospace and defence is projected to grow from approximately USD 28 billion in 2025 to USD 65 billion by 2034, representing a compound annual growth rate of 9.91%. Notably, North America is a significant contributor to this market, accounting for USD 10.43 billion and growing even faster at a rate of 10.02%. In parallel, firms in the defence sector, such as Lockheed Martin and RTX Corporation, are making explicit moves to embed AI, autonomy, and data fusion across platforms. For instance, Lockheed's Aeronautics division reported 12% year-over-year sales growth in Q3 2025 amid these trends (Barron, 2025).

Given these twin trends (i) the convergence of defence spending and AI deployment, and (ii) the thematic growth of AI-targeted stocks, it is timely and vital to explore the comovement between U.S. defence and global AI stocks and how their comovements respond to global risk factors and the occurrence of extreme events. Global risk factors can significantly alter the co-movement between global AI stocks and U.S. defence stocks by amplifying or dampening their time-varying correlations. Rising geopolitical risk is expected to strengthen the link between the two sectors, as defence stocks benefit from heightened security concerns (e.g., Gheorghe and Panazan, 2024; Panazan and Gheorghe, 2025; Song et al., 2025). At the same time, AI firms gain momentum from increased integration of military technology. Zhang et al. (2022), Wang and Yun (2023), Klein (2024), and Song et al. (2025) showed that defence stocks are substantially affected by geopolitical risk. However, no prior work has examined the impact on AI-defence correlations. Financial stress is linked to geopolitical risks and stock market volatility (e.g., Neto, 2025), which may increase correlations through broad risk-off behaviour, thereby reducing diversification benefits. Oil volatility affects defence procurement costs and macro uncertainty, indirectly influencing market sentiment toward technology sectors (e.g., Góes et al., 2022). Meanwhile, trade policy uncertainty reshapes global supply chains and technology flows (e.g., Lin et al., 2022 and Sayal, 2025), influencing investor expectations and potentially tightening the interdependence between AI innovations and defence capabilities.

To date, the question of how global risk factors and extreme events impact the dynamic correlations between global AI and U.S. defence stocks remains unanswered. Most existing studies have focused primarily on the correlation between AI and traditional assets (e.g., Klein, 2024 and Urom et al., 2024) or have explored the effects of geopolitical risks, economic uncertainties, and other significant events on defence stocks (e.g., Zhang et al., 2022; Wang and Yun, 2023; Covachev and Fazakas, 2024; Gheorghe and Panzan, 2024; Panzan and Gheorghe, 2025; Ozcelebi et al., 2025; and Song et al., 2025). Or AI stocks (McClellan, 2025). To our knowledge, no prior research has explicitly examined the influence of these global risk factors on the dynamic correlations between global AI and U.S. defence stocks. This paper aims to fill the gap in the literature and makes several meaningful contributions.

To address the research question, we utilise a three-stage complementary approach. First, we implement multivariate GARCH models with dynamic conditional correlation (DCC) and asymmetric DCC (ADCC) to estimate the time-varying correlations. The DCCs and ADDCs are integrated into a GARCH-X model that also includes global risk drivers such as oil price volatility, equity market volatility, geopolitical risk, financial stress, and trade-policy uncertainty jointly in the conditional mean and variance processes. Next, we extend the analysis beyond the standard time domain into the time-frequency domain using the wavelet quantile correlation (WQC) approach. This allows us to investigate whether the DCCs' dependence on risk factors varies by investment horizon (short-, medium-, or long-term) and by tail behaviour (left-, median-, or right-tail quantiles).

In doing so, this paper contributes to the literature on horizon-specific and quantile dependence, particularly in tail-risk modelling, by applying these concepts to the defence and AI nexus. This is particularly relevant empirically, as the defence sector may behave differently from the pure technology sector during crises or extreme events. Additionally, the AI sector may respond more strongly to shocks in policy, technology, or commodities. This suggests a non-uniform dependence structure across different horizons and quantiles. By combining DCC/ADCC-GARCH with WQC, this study offers new evidence on dependence dynamics, contributing to both portfolio risk management and a broader understanding of cross-sector contagion in an era characterised by AI-driven defence spending.

The paper progresses as follows. Section 2 briefly reviews prior studies and highlights the study's main contribution. Section 3 presents the datasets and the methods used. Section 4 reports and discusses the main findings. Conclusions and policy implications are conveyed in section 5.

2. REVIEW OF PRIOR STUDIES

The present table reviews prior studies.

Table 1: Review of prior studies.

Authors	Sample and data	Methos	Key findings
Gubareva et al., (2024)	2018 to 2023. Stocks, debt, currency, oil, AI, clean technology stocks in the US	Generalized quantile-on-quantile connectedness method that assesses variable cross-quantile interdependencies.	• AI is evidenced as net transmitter of risk across all quantiles, the oil market and USD markets. • AI, clean technologies and stocks, are more transferring risk than debt, currency, or other commodity markets.
Capelle-Blancard, and Couderc (2007).	59 largest public listed firms in the defense industry. 1995-2005	Event study method.	• Defense stocks have common drivers as other stocks. • A key role of geopolitical risk is highlighted.
Apergis et al. (2017)	24 global defense firms, 1985:1 - 2016:06	*k*-th-order nonparametric causality test	• GRP index does predict realized volatility in 50% of the companies.
Zhang et al. (2022)	GPR index Aerospace sector returns, 36 global defence and Aerospace compagnies	Wavelet coherence method	• The GPR-Aerospace return comovements increase during the ionset of the Russo-Ukranian war. • Flight to arms phenomenon was identified. • Comovements are more pronounced for European and US arespace compagnies at the medium and longer scales.
Urom et al. (2024)	AI stocks and eight energy focused stocks	Wavelet coherence, Cross-Quantilogram, and TVP-VAR model	• AI and energy stocks' connectedness intensifies during medium long-term investment horizons. • The relationship is amplified during the COVID-19 pandemic.
Klein (2024)	GPR index, intraday data, defence stock prices.	Hierarchical clustering method	• GPR proxies have differ in terms of their effect on short-term predictions of intraday volatility.
Wang and Yun, (2023).	Chinese defence sector (publicly listed firms)	Rolling window Granger Causality tests	• A nonlinear association is evidenced between geopolitical risk and the defence industry's stock market.

			• Geopolitical risk is evidenced as a predictor of the market return of the defence sector.
Covachev, and Fazakas (2024).	European defence stock January 2019- August 2023.	Event study	• The Rosso-Ukrainian war was followed by an increase (12%) of military related stocks.
Gheorghe and Panzan (2024)	75 global defence compagnies GPR index	Wavelet coherence analysis	• The Russo-Ukrainian war has affected the defense stocks by 81.4% of global defense firms. • The COVID-19 had moderately affected defense stock returns.
Panzan and Gheorghe (2025)	January 2014 to March 2024, 75 defence firms from 14 countries	Wavelet methos and phase differences	• Innovation has higher impact compared to geopolitical risk factors
Ozcelebi et al., (2025)	Technology ETFs Uncertainty indexes January 2018 to September 2023.	Quantile frequency interconnections Quantile frequency spillover Wavelet coherence	• Under normal market conditions, short-term connectedness is more relevant. • Most technology ETFs are net spillover transmitters and uncertainty indices net spillover receivers, showing contagion risk in ETF investments.
Song et al. (2025)	US defense ETFs GPR index	Wavelet-based Quantile to Quantile method	• Over the short-term • GPR compels investors to treat defence stocks as safe-haven assets. • In the medium and long term, geopolitical tensions have adverse effects on defense stocks.

From the above review of prior studies, a few comments emerge. First, previous studies highlight strong volatility spillover effects and correlations across defence (Apergis et al. 2017; Wang and Yun, 2023; and Covachev and Fazakas 2024), technology (Gubareva et al., 2024), energy (Zhang et al., 2022 and Urom et al. 2024) and geopolitical extreme incidents, particularly during conflict episodes and spikes of global uncertainty (Gheorghe and Panzan 2024; Klein 2024, Song et al., 2025; Ozcelebi et al., 2025 and Panazan and Gheorghe 2025). Prior works are predominantly focused on asset return and volatility connectedness using various empirical frameworks, or on the impact of geopolitical risk on defence or technology stocks in isolation. Second, a handful of works have studied dynamic correlations using single or broad technology indexes, mainly focusing on a single risk factor as the driver (geopolitical risk). Factors such as oil market volatility, financial stress, trade policy uncertainty, and equity market volatility have not been jointly considered in a unified model. More importantly, no prior study has jointly examined how global risk factors and extreme events shape the time-varying correlations between global AI stocks and US defence stocks, nor has it investigated their correlations across investment horizons and market conditions. This paper fills a gap in the literature by offering a first empirical essay on the global AI-US defence stock dynamic relationships using three complementary frameworks: the multivariate GARCH model under DCC and ADCC, the GARCH-X model, and the WQC. In doing that, the present study advances the literature from static or partial analyses toward a state-dependent, multi-horizon understanding of how strategic sectors co-move under global uncertainty.

3. DATA AND METHODS

For the global Robotics/IA stocks (IA Stocks), we employ two key indexes: the Global X Robotics and AI ETF (BOTZ) and the iShares Robotics and AI ETF (IRBO). These robotics and AI exchange-traded funds track the performance of leading global companies across autonomous vehicles, drones, healthcare robotics, AI software and algorithms, industrial automation, and manufacturing robotics. The iShares Robotics and AI index comprises firms from both developed and emerging markets that are likely to benefit from long-term growth driven by innovation in robotics, automation, and AI. Additionally, we consider two United States defence industry indexes (US Defence Stocks): the iShares US Aerospace & Defence ETF (ITA) and the SPDR S&P Aerospace & Defence ETF (XAR). All-time series data for these indices were sourced from Investing.com. The indices are denominated in US dollars and cover the period from November 3, 2016, to October 21, 2025, yielding a total of 2,278 observations. Table 2 reports the descriptive statistics of the logarithmic daily returns. Fig. 1 shows the time series movement.

Table 2: Descriptive statistics

	IA stocks		US Defence stocks	
	BOTZ	IRBO	ITA	XAR
Mean	0.017465	0.020810	0.023032	0.025906
Median	0.042156	0.051455	0.040633	0.036697
Maximum	5.205617	3.940221	5.033052	4.191555
Minimum	-5.752464	-4.467920	-6.926175	-6.201948
Std. Dev.	0.710021	0.577248	0.644085	0.669863
Skewness	-0.335372	-0.586213	-0.833392	-0.669117
Kurtosis	10.30974	7.642403	19.08008	13.46626
Jarque-Bera	5055.946***	2151.269***	24523.06***	10446.80***

Notes: (***) indicates (<0.001).

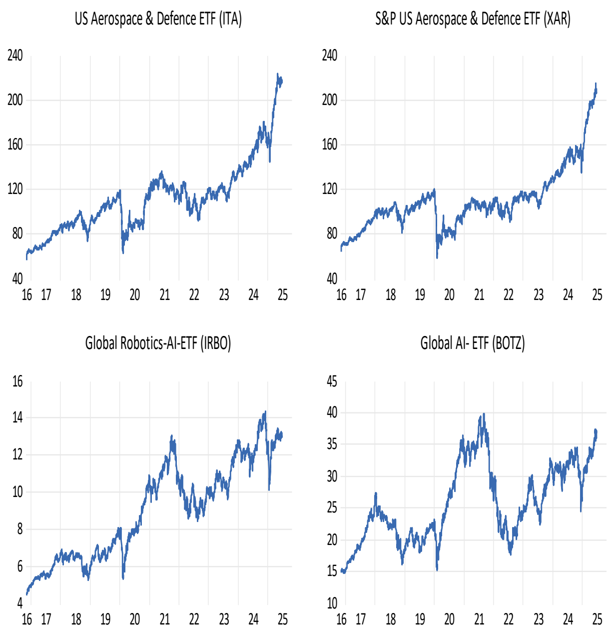


Figure 1: Time movements of the AI and US defense stock indexes.

The correlation dynamics of global AI-US defence stocks are analysed using the GARCH-ADCC and DCC models proposed by Engle (2002) and Cappiello et al. (2006). The ADCC model is better suited than the standard DCC for analysing the dynamic correlation as it may respond more strongly to adverse shocks such as geopolitical tensions, market stress, or escalations in global risk (e.g., Cappiello et al., 2003). These events typically cause correlations to increase asymmetrically, a pattern that the ADCC model explicitly captures, whereas the symmetric DCC does not.

4. EMPIRICAL RESULTS

4.1. The global AI- US defence stocks correlations

In short, the GARCH-DCC model combines the GARCH model with a dynamic conditional correlation (DCC) structure, while each asset (AI and defence stocks) evolves independently. The time-varying pattern of correlations allows us to understand how market dynamic linkages respond to external shocks from exogenous risk factors (geopolitics, oil volatility, and economic uncertainties). The GARCH-ADCC (asymmetric dynamic correlation) extends the DCC framework by accounting for asymmetric behaviour in time-varying correlations. This framework recognised that negative shocks inherent in market downturns tend to amplify correlations more than the same-magnitude positive shocks. More importantly, the GARCH-ADCC accounts for leverage effects in volatility, which may provide deeper insights into asset-class comovements and contagion during turbulent market conditions. The estimation results of the GARCH-DCC/ADCC are displayed in Table 3 (reported in Appendix I).

From these results, the estimated parameters α and β are statistically significant at the 1% level under both DCC and ADCC specifications, providing strong evidence of volatility clustering. The asymmetry parameter is negative and significant only for BOTZ-XAR and IRBO-XAR, indicating that these couples are asymmetrically affected by positive and negative shocks. The estimated ADCC and DCC values show that BOTZ is strongly and positively correlated with both ITA and XAR in both specifications. The average dynamic correlations range from 0.450 to 0.544. However, IRBO is weakly and positively correlated with both ITA and XAR for both ADCC and DCC specifications, with only the ADCC specifications being statistically significant at the 5% and 10% levels.

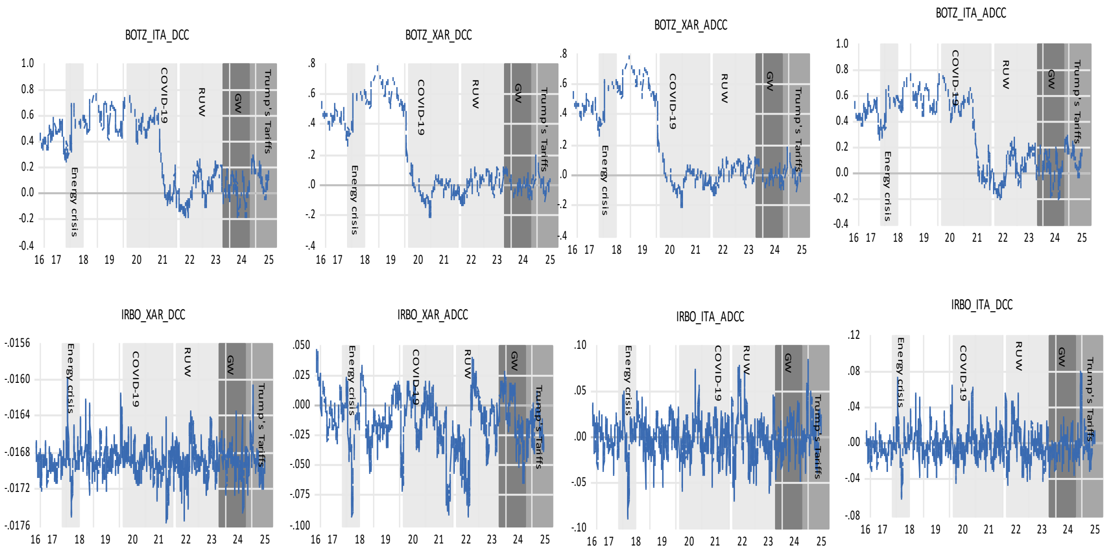


Figure 2. Time movements of the IA-US Defence stocks, DCCs, and ADCCs.

From Fig. 2, we observe that both BOTZ-ITA and BOTZ-XARA exhibit unstable relationships. From 2016 to 2020, a moderate positive correlation was observed, followed by a sharp decline, which aligns with the COVID-19 pandemic and the oil market crash. Starting in 2022, DCC and ADCC values have

$$DCC_{i,t} = \mu_i + \rho DCC_{i,t-1} + \delta X_t + \varepsilon_{i,t} \quad (1a)$$

$$ADCC_{i,t} = \mu_i + \rho ADCC_{i,St-1} + \delta X_t + \varepsilon_{i,t} \quad (1b)$$

remained low but have reacted sporadically to news events and geopolitical tensions, notably the Russo-Ukrainian war (February 2022). The DCC and ADCC between IRBO-ITA and IRBO-XARA are low and volatile, showing no evidence of lasting regime shifts.

4.2. Extreme events and drivers of the DCCs and ADCCs: GARCH-X approach

Table 4: Descriptive statistics of the DCCs and ADCCs

	DCC				ADCC			
	BOTZ-ITA	BOTZ-XAR	IRBO -ITA	IRBO -XAR	BOTZ -ITA	BOTZ -XAR	IRBO -XAR	IRBO -ITA
Mean	0.450	0.544	0.001	0.016	0.531	0.542	0.028	0.012
Max	0.801	0.779	0.079	-0.015	0.793	0.783	0.046	0.082
Min	-0.198	-0.217	-0.061	-0.017	-0.218	-0.217	-0.092	-0.090
S.D.	0.271	0.277	0.016	0.000	0.275	0.278	0.023	0.021
Sk.	-0.033	0.608	0.720	0.451	-0.095	0.612	-0.540	0.004
K.	1.670	1.770	5.181	5.820	1.645	1.778	3.5618	4.0731
J-B	166.3	280.7	641.22	822.88	175.56	280.74	139.25	108.07
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: figures between parentheses indicate the significant at (<0.001). J-B is the Jarque-Bera normality test. S.D. is the standard deviation. K. is the Kurtosis statistic. Sk. Refers to the Skewness statistic.

To assess the influence of global risk factors, geopolitical and trade uncertainties, and extreme events on the DCC and ADCCs, we extend the GARCH-DCC/ADCC baseline model by estimating a new GARCH-X model (e.g., Han 2015). The choice of the GARCH-X model is well motivated by the presence of heteroscedasticity and volatility clustering in both the DCC and the ADCC time series, as shown in Table 4. The augmented mean equation for each asset DCC/ADCC is specified as in Equations (1a and 1b):

In the above Equations, X_t refers to a vector of exogenous risk factors at time (t), including the financial stress index (FSI), geopolitical risk index (GPR), trade policy uncertainty (TPU), oil price volatility (OVX), and stock index volatility (SVI). The conditional variance is written as follows:

$$h_{i,t}^2 = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2 I_{t-1}\theta' X_t \quad (2)$$

where θ measures the impact of the risk factors on the conditional variance of each asset. As in the baseline model, the indicator function I_{t-1} if $\varepsilon_{t-1} < 0$ captures asymmetric volatility responses to adverse shocks.

The GARCH-X estimates are reported in Table 5 (reported in Appendix II). We incorporate exogenous risk factors into the mean equation (panel a). Panel (b) reports a second specification that adds event-specific dummy variables to the conditional variance to capture sharp, short-term volatility shifts triggered by major systemic shocks. We consider four extreme events: the COVID-19 pandemic (March 11, 2020), the Russo-Ukrainian War (RUW) (February 24, 2022), the Gaza war (GW) (October 7, 2023), and Trump's tariff shocks (April 7, 2025).

The GARCH-X outcomes (panel a) underscore the strong persistence of the ADCCs, with the estimated parameter for the lagged values being statistically significant and very close to 1, indicating that external shocks to comovements dissipate slowly. Among global risk factors, only OVX emerges as a substantial driver of ADCC. The estimated parameter is positively signed, implying that oil-driven macro-uncertainty is strengthening the dynamic correlation between global AI and US defence stocks. Conversely, the other selected factors turn out to be insignificant. The examination of the augmented conditional variance equation (panel b) reveals that the dummy variables for the RUW and the COVID-19 pandemic are positive and statistically significant, highlighting the positive impact of these extreme events on volatility and dynamic correlations between global AI stocks and US defence stocks. This result can be explained as follows. Defence stocks are sensitive to spikes in geopolitical risk, often experiencing substantial increases in military spending as a result (e.g., Gheorghe and Panazan, 2024; Chatziantoniou et al., 2025; and Panazan and Gheorghe, 2025). Concomitantly, AI and high-tech stocks react to shifts in investor sentiment triggered by geopolitical events and global uncertainty, such as the COVID-19 pandemic. Due to their consistent exposure to risk, the correlation between AI and defence stocks tends to strengthen volatility. More importantly, the dummy variable representing the recent Trump trade tariffs is significant and negative, indicating a notable impact on ADCC's volatility. This finding can be attributed to spikes in trade uncertainty, which affect AI (Gao et al., 2024) and US defence stocks differently, thereby weakening their shared risk exposure and reducing their interdependence volatility. Consequently, investors may interpret tariff shocks differently when assessing the performance of AI companies versus US defence firms. Taken together, the results of the GARCH-X model analysis reveal that the global AI-US defence stocks nexus is structurally persistent, sensitive to volatility in oil markets, and episodically destabilised by significant global geopolitical spikes and extreme global risk events.

4.3. Global AI -US Defence Stocks Drivers: A Multiscale Quantile Analysis

To enhance the multivariate GARCH-DCC-ADCC and GARCH-X analyses, we complement them with WQC to capture time–frequency correlations across different market states (e.g., Ren et al., 2022 and Abakah et al., 2024). Briefly, the WQC method is a statistical technique that analyses how two variables (ADCCs and exogenous variables) move together across various time horizons and under different market conditions (bearish and bullish). Wavelets decompose time series into short- and long-term components (horizons), while quantiles capture market conditions and global extreme events. Therefore, by combining the two ideas, the WQC demonstrates the strength of the relationship across various market conditions (calm, turbulent, or crisis) and how this strength varies in the short and long term. As a result, the WQC is a suitable tool for understanding the dependence structure between two selected variables during extreme events and across various time scales. By accounting for wavelet scales and quantiles, WQC reveals the nonlinear, scale-dependent, and asymmetric influence of exogenous factors, offering a more comprehensive picture of their impact on ADCCs. Across all heatmaps (Fig. 3, reported in Appendix III). In Fig. 3, first row, we observe that GPR-ADCCs are heterogeneous across time scales, investment horizons and market conditions. GPR plays a significant, regime-dependent role in driving asymmetric correlations. Its effect is more pronounced in the tails (turbulent conditions), suggesting a nonlinear, asymmetric impact on global AI and US defence stocks, potentially reducing the portfolio's diversification benefits during geopolitical risk episodes. It underscores the need for portfolio rebalancing and tail-risk hedging during GPR spikes. Similarly, TPU displays a nonlinear, regime-dependent effect on ADCCs. Its effect is to strengthen during high-uncertainty trade regimes and turbulent conditions, where regulatory risks and new U.S. trade tariffs affect both defence procurement and high-tech supply chains (see Klomp, 2025). Trade tariffs have become more than an economic tool; they have become an instrument of geopolitical leverage (see Global Defence Outlook, 2025). This pattern confirms that TPU serves as a structural global systematic risk factor shaping the co-movement of global AI-US defence stocks rather than a short-lived shock. The WQC heatmaps (third row) reveal that OVX exerts a nonlinear, state-dependent influence on ADCCs. Unlike geopolitical risk, dependence is predominantly localised in the middle quantiles and the extreme tails, underscoring that OVX oil does not affect correlations homogeneously across market conditions. However, its effect intensifies during periods of market stress or heightened uncertainty, possibly due to higher energy-related input costs. In the FSI heatmaps (fourth row), we observe that financial stress has a nonlinear, regime-dependent effect on the ADCC's structure. Its effect is most evident under extreme financial stress and tail market states. This result suggests that FSI may act as a systematic amplifier, attenuating the portfolio diversification benefits of AI-defence stocks during extreme conditions. The SVI heatmaps (fifth row) show that stock market volatility exerts a more substantial and homogeneous effect on the ADCCs than the other global risk factors, as the impact is observed across multiple quantile regions. This pattern suggests that stock volatility is perceived as a conduit for global uncertainty and investor fears, thereby strengthening the dependence structure between AI and the US defence markets, particularly during crisis periods.

5. MAIN CONCLUSIONS AND POLICY IMPLICATIONS

In this paper, we investigate the influence of global risk factors and extreme events on the time-varying correlations between US defence stocks and global artificial intelligence (AI) stocks, using daily data from November 2016 to October 2025. To our knowledge, this is the first study to tackle this topic in the defence-AI finance literature. In doing that, we proceed within three complementary frameworks. First, we implement multivariate GARCH models, including DCC and ADCC, to estimate time-varying correlations. Second, the DCCs and ADDCs are modelled using a GARCH-X model that includes global risk drivers such as oil volatility, equity market volatility, geopolitical risk, financial stress, trade-policy uncertainty, and other extreme events, simultaneously in the conditional mean and variance processes. Our main goal is to explore how global risk factors and extreme geopolitical incidents (the Russo-Ukrainian and Gaza wars), as well as global uncertainties such as COVID-19 and the recent Trump tariff decisions, affect the strength (GARCH-X mean equation) and the volatility of dynamic correlations (variance equation). Third, we extend the analysis beyond the standard time domain into the time-frequency domains using the WQC approach to investigate how global risk factors affect global AI-US defence stocks across investment horizons (short vs. long) and across various market conditions (tail behaviour).

Our analysis identifies several new insights. First, global AI stocks and US defence stocks are positively and moderately correlated, and their correlation exhibits a strong time-varying pattern. Second, among global risk factors, only oil market volatility is a substantial driver of dynamic correlation, indicating that oil-driven macro-uncertainty is strengthening the dynamic correlation between global AI stocks and US defence stocks. In contrast, the other risk factors are irrelevant. Third, extreme incidents such as the Russo-Ukrainian and Gaza wars, the COVID-19 pandemic, and recent tariff shocks associated with Trump's policies substantially impact the stability of defence-AI stock correlations. Fourth, in the time-frequency domain, the WQC method shows that the influence of all global risk factors on time-varying correlations is heterogeneous and varies across investment horizons and market conditions.

The above findings offer several implications for investors and policymakers. For portfolio managers, it is helpful to understand that AI-US defence stocks are moderately and positively correlated with significant time-varying patterns, implying that the nexus between the two sectors is not stable. Meaning that static AI-defence portfolio management strategies are insufficient, and that sovereign wealth funds, public, and institutional investors should implement dynamic hedging strategies, particularly during episodes of high geopolitical tensions and turbulent market conditions. Furthermore, oil market volatility is a significant risk factor, strengthening correlations and highlighting the role of energy market uncertainty as a key transmission channel. Therefore, policy makers are invited to account for energy market uncertainty in financial supervision models, stress testing, and defence-AI risk quantification. AI-US defence stocks’ relationships are substantially destabilised by extreme events such as the wars in Ukraine and Gaza and trade tariff shocks, implying that regulatory actions must be crisis-contingent to avoid excessive systemic risk. Finally, the time-frequency analysis reveals that the impacts of global risk factors differ across investment horizons, time scales and market conditions. These results imply that standard policy frameworks are inefficient, and that policymakers should have horizon-specific regulatory instruments and differentiate between short- and long-term investment strategies. Elaborating state-dependent risk management frameworks could improve resilience during periods of high uncertainty.

These new findings contribute to the AI-defence nexus literature and could be extended in several ways. The use of other AI or defence stock indexes and other sample periods helps assess the robustness of the results. Moreover, the use of different empirical frameworks, such as the Markov-switching or time-varying parameter autoregressive model (TVP-VAR), helps capture structural changes and shifts in behaviour in the dynamic correlations of the AI-Defence stock. The use of multiple and partial wavelets may help investigate the isolated and combined effects of each global risk factor on correlation in the time-frequency domain. Finally, extending the research to other markets and conducting a cross-country comparison, including analyses of Russia and China, may deepen understanding of the time-varying connectedness of AI-defence stocks.

This study offers a fresh and comprehensive interdisciplinary analysis of the time-varying connectedness between global AI stocks and US defence stock markets, with particular attention to their drivers of global risk. Thus, it provides a connection among technological innovation, financial market behaviours, and global geopolitics, and underscores how artificial intelligence is reshaping not only stock markets but also global securities and power issues. We believe this novel study will contribute to the academic discourse by better understanding the interconnections among technological advances, market dynamics, and broader societal transformations in an uncertain context of heightened geopolitical tensions and trade and economic uncertainties.

REFERENCES

Abakah, E. J. A., Goodell, J. W., Sulong, Z., & Abdullah, M. (2024). Wavelet quantile correlation between DeFi assets and banking stocks. Finance Research Letters, 70, 106272. https://doi.org/10.1016/j.frl.2024.106272

Apergis, N., Bonato, M., Gupta R., and Kyei, C. (2017). Do geopolitical risks predict stock returns and volatility of leading defence companies? Evidence from a nonparametric approach. Defence and Peace Economics 29, (6), 684-696. https://doi.org/10.1080/10242694.2017.1292097

Capelle-Blancard, G., & Couderc, N. (2007). What drives the market value of firms in the defence industry? Review of Financial Economics, 17(1), 14-32. https://doi.org/10.1016/j.rfe.2007.02.001

Cappiello, L., K., Arjan; G., Bruno and Manganelli, S. (2006), Financial Integration of New EU Member States. ECB Working Paper No. 683, Available at SSRN: https://ssrn.com/abstract=936591 or http://dx.doi.org/10.2139/ssrn.936591

Chatziantoniou, I., Gabauer, D., & Stenfors, A. (2025). US sectoral stock market volatility and geopolitical risk categories. Finance Research Letters, 76, 106916. https://doi.org/10.1016/j.frl.2025.106916

Covachev, S., and G. Fazakas, (2024). The effects of the Russia–Ukraine war and the Wagner Group coup on defense stocks in Europe: an event study analysis, Studies in Economics and Finance, 42, (1) 31-42, https://doi.org/10.1108/SEF-11-2023-0675.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. Journal of Business & Economic Statistics, 20(3), 339–350. http://www.jstor.org/stable/1392121

Gao, W., Zhang, L., Zhang, H., & Zhang, H. (2024). The role of trade policy uncertainty on contemporaneous and lagged connectedness between critical raw materials and high-tech markets: Evidence from China. Resources Policy, 98, 105356. https://doi.org/10.1016/j.resourpol.2024.105356

Gheorghe, C., & Panazan, O. (2024). Investigating the effect of geopolitical risk on defence companies' stock returns. Heliyon, 10(24), e40974. https://doi.org/10.1016/j.heliyon.2024.e40974

Góes, C., & Bekkers, E. (2022). The Impact of Geopolitical Conflicts on Trade, Growth, and Innovation. ArXiv. https://arxiv.org/abs/2203.12173

Gubareva, M., Shafiullah, M., & Teplova, T. (2024). Cross-quantile risk assessment: The interplay of crude oil, artificial intelligence, clean tech, and other markets. Energy Economics, 141, 108085. https://doi.org/10.1016/j.eneco.2024.108085.

Han, H., and Kristensen, D. (2014). Asymptotic Theory for the QMLE in GARCH-X Models with Stationary and Nonstationary Covariates. Journal of Business and Economic Statistics, 32, 416-429. https://doi.org/10.1080/07350015.2014.897954

Klein, T. (2024). Investor behavior in times of conflict: A natural experiment on the interplay of geopolitical risk and defense stocks. Journal of Economic Behavior & Organization, 222, 294-313. https://doi.org/10.1016/j.jebo.2024.04.020

Klomp, J. (2025). Trump tariffs and the U.S. Defense industry. PLOS ONE, 20(1), e0313204. https://doi.org/10.1371/journal.pone.0313204

Lin, B., Yuan, L., & Lu, B. (2022). How Does Trade Policy Uncertainty Affect Supply Chain Efficiency: A Case Study of Listed Companies of the Chinese Port Industry. Sustainability, 15(9), 7140. https://doi.org/10.3390/su15097140

McClellan, M. (2025). AI and Financial Fragility: A Framework for Measuring Systemic Risk in Deployment of Generative AI for Stock Price Predictions. Journal of Risk and Financial Management, 18(9), 475. https://doi.org/10.3390/jrfm18090475

Neto, D. (2025). Buy when there's blood in the streets: How geopolitical adverse events can push defense stock returns to the extreme. European Journal of Politica Economy, 90, 102771. https://doi.org/10.1016/j.ejpoleco.2025.10277

Ozcelebi, O., McIver, R., & Kang, S. H. (2025). The dynamics of frequency connectedness between technology ETFs and uncertainty indices under extreme market conditions. Financial Innovation, 11(1), 1-33. https://doi.org/10.1186/s40854-025-00760-5

Panazan, O., & Gheorghe, C. (2025). Impact of geopolitical risks and innovation on global defense stock return. PLOS ONE, 20(2), e0312155. https://doi.org/10.1371/journal.pone.0312155

Ren, X., Li, Y., Yan, C., Wen, F., & Lu, Z. (2022). The interrelationship between the carbon market and the green bonds market: Evidence from wavelet quantile-on-quantile method. Technological Forecasting and Social Change, 179, 121611. https://doi.org/10.1016/j.techfore.2022.121611

Sanyal, A. (2025). Caught in the crossfire: How trade policy uncertainty impacts global trade. International Economics, 184, 100621. https://doi.org/10.1016/j.inteco.2025.100621

Song, X., Su., C.W., and Qin M., (2025). Geopolitical storm approaches: can defence stocks serve as a safe haven? Defence and Peace Economics 1,16, https://doi.org/10.1080/10242694.2025.2573012

Urom, C., Ndubuisi, G., Mzoughi, H., and Guesmi, K. (2024). Exploring the coherence and predictability between the stocks of artificial intelligence and energy corporations. Financial Innovation, 10(1), 1-31. https://doi.org/10.1186/s40854-024-00609-3

Wang Y., and L., Yun, (2023). Does geopolitical risk influence China's defence sector returns? Peace Economics, Peace Science, and Public Policy, 29(3), 279-287. https://doi.org/ 10.1515/peps-2023-0027

Xiao, L., D., L., Da Silva, L., Scarazzato, Z., Karim, and J.G., Ricard (2025). Trends in world military expenditure, 2024. Siprit Fact Sheet, Report available on the link: https://www.sipri.org/sites/default/files/2025-04/2504_fs_milex_2024.pdf

Zhang, Z., Bouri, E., Klein, T., and Jalkh, N. (2022). Geopolitical risk and the returns and volatility of global defense companies: A new race to arms? International Review of Financial Analysis, 83, 102327. https://doi.org/10.1016/j.irfa.2022.102327.

Appendix I

Table 3: The GARCH-DCC and ADCC estimation results

	BOTZ-ITA		BOTZ-XAR		IRBO-ITA		IRBO-XAR	
	DCC	ADCC	DCC	ADCC	DCC	ADCC	DCC	ADCC
Panel a: parameters' estimates								
α	0.028*** (3.35)	0.026*** (2.88)	0.018*** (4.83)	0.017*** (4.67)	0.008** (1.86)	0.012** (1.97)	-0.01*** (-2.79)	0.006** (1.99)
β	0.967*** (9.32)	0.968*** (8.05)	0.981*** (23.3)	0.983*** (31.6)	0.861*** (12.63)	0.882*** (9.33)	0.953*** (4.01)	0.956*** (5.54)
γ	-	-0.005 (-0.79)	-	-0.008*** (4.65)	-	-0.008 (-0.55)	-	-0.008** (-2.32)
ρ	0.450*** (3.81)	0.537*** (3.31)	0.544*** (2.73)	0.542*** (2.56)	0.0018 (0.008)	0.012 (0.29)	0.016* (1.76)	0.028** (1.71)
Panel b: diagnostics								
Akaike	3.156	3.157	3.426	3.427	3.056	3.057	3.231	3.231
Shibata	3.156	3.156	3.426	3.427	3.056	3.057	3.231	3.231
H-Q	3.166	3.168	3.431	3.441	3.066	3.068	3.246	3.245

Notes: The t-student values are in parentheses. H-Q is the Hannan-Quinn information criteria. (*) indicates (<0.1), (**) shows (<0.05), and (***) indicates (<0.001).

Appendix II

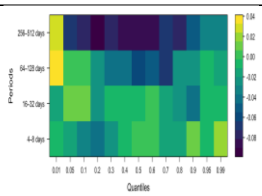
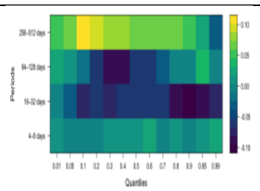
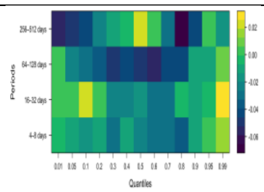
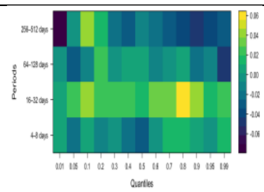
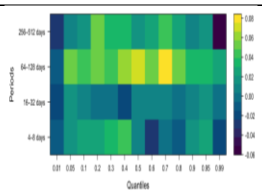
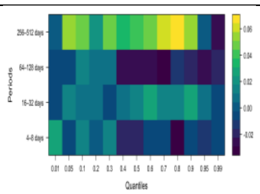
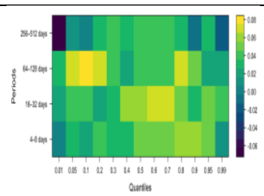
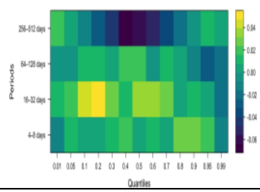
Table 5: GARCH-X estimation results for the ADCC with global risk factors and event drivers

	BOTZ-ITA	BOTZ-XAR	IRBO-ITA	IRBO-XAR
Panel a: The GARCH-X conditional mean equation				

α_0	0.0011 (1.65)	0.0009 (1.21)	2.3E-05 (0.05)	2.5E-05 (0.05)	-0.0004*** (2.82)	-0.0004*** (-2.59)	-1.7E-06 (-0.00)	1.8E-05 (0.08)
$ADCC_{t-1}$	0.9953*** (517.20)	0.9959 (521.44)	0.9976*** (638.88)	0.9978*** (753.77)	0.9667*** (171.54)	0.9673*** (192.70)	0.8917*** (87.06)	0.8947*** (94.51)
FSI	0.0001** (2.03)	6.78E-07 (0.00)	1.4E-05 (0.37)	1.43E-05 (0.39)	-1.93E- (-0.05)	-0.0001 (-1.51)	6.2E-07 (0.01)	9.7E-07 (0.01)
GPR	-0.0001 (-0.25)	-0.0001 (-0.23)	0.0005 (1.19)	0.0004 (1.02)	-0.0001 (-0.99)	-0.0001 (-1.51)	1.99E- (0.08)	8.52E-05 (0.40)
TPU	0.0003 (0.86)	0.0003 (0.81)	6.42E-05 (0.20)	9.89E-05 (0.33)	1.12E-05 (0.11)	-3.11E-05 (-0.35)	-0.0001 (-0.89)	-0.0001 (1.01)
OVX	0.0056** (2.07)	0.0058*** (2.34)	-0.0003 (-0.14)	0.0009 (0.47)	0.0002 (0.40)	0.0002 (0.46)	**0.0015*** ** (2.53)	-0.0011 (-1.15)
SVI	-0.000152 (-0.15)	7.59E-06 (0.07)	1.74E-05 (0.19)	3.42E-05 (0.42)	1.78E-05 (0.52)	2.08E-05 (0.55)	6.64E-05 (1.21)	5.32E-05 (0.99)
Panel b: The GARCH-X conditional variance								
$Cst.$	0.0001*** (7.23)	0.0002*** (7.83)	0.0002*** (19.36)	0.0002*** (27.15)	2.3E-05*** (2.14)	2.1E-05*** (3.97)	2.3E-06*** (11.38)	4.2E-06*** (7.36)
a	0.0710*** (9.72)	0.0836*** (9.96)	0.0681*** (10.73)	0.0927*** (12.53)	-0.010*** (-5.42)	-0.0179*** (-8.38)	0.0014*** (2.98)	-0.0055*** (7.36)
b	9.7231*** (18.18)	0.2541*** (2.91)	-0.0187*** (-0.38)	-0.0629*** (-2.34)	0.2932*** (2.87)	0.1027*** (3.43)	0.9742*** (365.3)	-0.0055*** (115.58)
$dum_{COVID-19}$	-	5.39E-06 (0.39)	-	0.0001*** (10.65)	-	1.3E-05*** (3.49)	-	2.7E-06*** (5.64)
dum_{UKW}	-	0.0001*** (5.51)	-	0.0001*** (7.97)	-	2.36E-05 (3.69)	-	2.5E-06*** (5.62)
dum_{GW}	-	-0.0000 (-0.20)	-	8.18E-05*** (5.23)	-	1.3E-05*** (3.51)	-	1.4E-06*** (4.21)
$dum_{T.tarifs}$	-	-9.85E-05** (-2.60)	-	-0.0006*** (-3.74)	-	-5.2E-06*** (-2.10)	-	-9.7E-07*** (-2.45)
Panel c: Diagnostics								
Akaike	3.15	3.15	3.42	3.41	3.43	3.43	3.24	3.24
Shibata	3.15	3.15	3.42	3.41	3.43	3.43	3.24	3.24
H-Q	3.17	3.17	3.44	3.43	3.44	3.44	3.25	3.25

Notes: Figures between parentheses are the t-statistic, while H-Q refers to Hannan-Quinn information criteria. **(***)** (<0.001).

Appendix III

GPR vs. IRBO-XAR' ADCC	**GPR** vs. IRBO-ITA ADCC	**GPR** vs. BOTX-ITA' ADCC	**GPR** vs. BOTX-XAR' ADCC
			
TPU vs. IRBO-XAR' ADCC	**TPU** vs. IRBO-ITA ADCC	**TPU** vs. BOTZ-ITA' ADCC	**TPU** vs. BOTZ-XAR'ADCC
			
OVX vs. IRBO-XAR' ADCC	**OVX** vs. IRBO-ITA ADCC	**OVX** vs. BOTZ-ITA' ADCC	OVX vs. BOTZ-XAR'ADCC

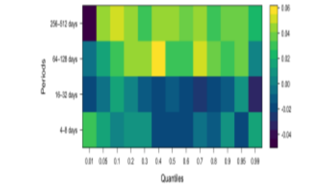
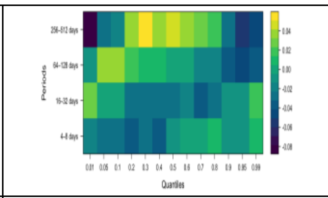
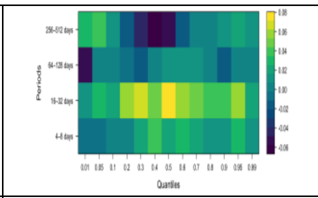
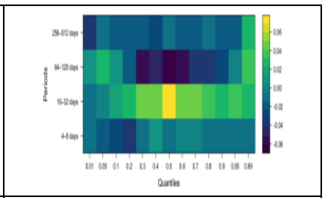
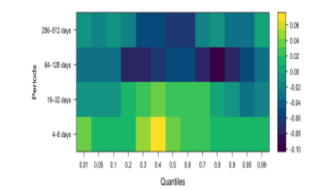
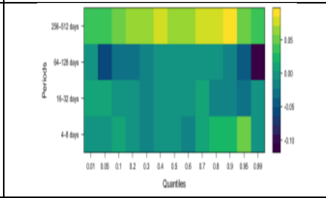
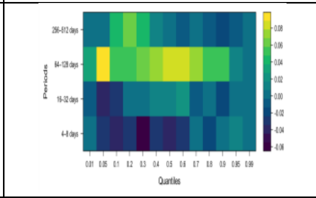
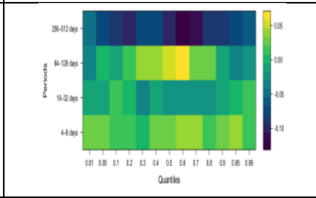
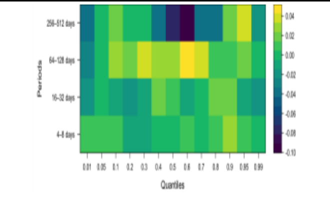
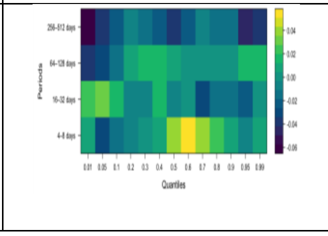
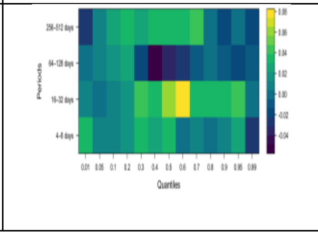
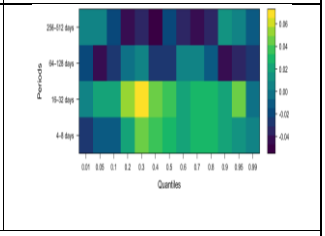
			
FSI vs. IRBO-XAR’ ADCC	**FSI** vs. IRBO-ITA ADCC	**FSI** vs. BOTZ-ITA’ ADCC	**FSI** vs. BOTZ-XAR’ADCC
			
SVI vs. IRBO-XAR’ ADCC	**SVI** vs. IRBO-ITA ADCC	**SVI** vs. BOTZ-ITA’ ADCC	**SVI** vs. BOTZ-XAR’ADCC
			

Figure 3. WQC of risk factor drivers of global AI and US defence ADCCs

Notes: The x-axis indicates quantiles ranging from 0.1–0.9. ; the y-axis portrays the MODWT scales ranging from 1 to 9, (short, medium and long term investment horizons). The colored bar code bar shows the strength of the correlation.