The Influence of Global Risks on Supply Chain Tokens' Intra-Market Dynamics

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Received: 6 June 2025 | Revised: 19 June 2025, 22 June 2025, 12 August 2025, and 26 August 2025 | Accepted: 30 August 2025

 DOI: https://doi.org/10.48084/etasr.12593

ABSTRACT

This study provided the first assessment of how the global risk factors influence the intra-market connectedness of Supply Chain Tokens (SCTs). Specifically, the Economic Policy Uncertainty (EPU), Trade Uncertainty Index (TUI), and Geopolitical Risk (GPR) were investigated on the time-varying equicorrelations of SCTs, including XYO Network (XYO), CargoX (CXO), Morpheus Network (MNW), VeChain (VET), and OriginTrail (TRAC) between 2018 and 2025. Using a multivariate GJR-GARCH mode, the results indicated that SCTs exhibited volatile but strong correlations ranging between 0.3 and 0.8. The correlations intensified during extreme market events, like the COVID-19 outbreak, the Gaza-Israel conflict, and the ongoing Russo-Ukrainian war. GPR enhanced the strength of the correlation, while EPU and TUI did not exhibited any significant impact. Furthermore, the extreme events during the sample period had no influence on the correlation's strength while reducing the time-varying instabilities. These findings offered insightful implications for tokens' traders, portfolio managers, and regulators of the SCTs' market, particularly concerning the market integration, hedging strategies, and overall market stability.

Keywords-geopolitical risk; trade uncertainty index; economic policy uncertainty; supply chain tokens; extreme events; equicorrelation; GJR-GARCH model

I. INTRODUCTION

The global supply chains have faced significant disruptions, primarily due to geopolitical tensions, economic uncertainties, and shifts in the international trade policies [1-5]. As firms aim to streamline their operations, the role of blockchain technology has gained attention from both researchers and practitioners [6, 7]. With their ability to provide secure payments while enhancing the visibility, transparency, and traceability, blockchain-based SCTs are being investigated as viable digital instruments to mitigate the adverse effects of the global uncertainties [8, 9]. However, their implementation in the supply chain operations is still in its early stages, and the market continues to face challenges from the global uncertainties. The interest of tokens' behavior in financial markets has also increased in academic circles, with two main streams emerging. The first examines the connectedness between cryptocurrencies and traditional financial assets or commodities [10-14], while the second focuses on the intra-cryptocurrency market dependence structure [14-18]. This study investigates how the GPR, EPU, and TUI contribute to the SCTs' intra-market dynamics. Specifically, this study addresses the following research questions: How do these factors affect SCTs' co-movements, and how is this dependence evolving during extreme market conditions? This is the first empirical study to explore these questions within in the context of the SCTs' market.

II. UNDERPINNINGS AND PRIOR STUDIES

In this section, various economic, financial, and organizational theories were explored to explain how GPR, economic uncertainty, and trade policy shifts influence the dynamics of SCT market.

A. Geopolitical Risk and the SCT Nexus

The GPR) index refers to adverse events, such as wars, terrorism, political instability, and state tensions that disrupt the peaceful course of international relations [19]. Based on the Game Theory and Composite Network Congestion Games, players choose to decentralize their decisions, which can affect both their own outcomes and those of others [20, 21]. The escalation of GPRs can lead to a fragmentation of the global trade infrastructure, prompting firms to avoid the dependence on specific countries. In this challenging environment, firms are encouraged to adopt blockchain-based technologies, including SCTs, to enhance their independence while reducing the exposure to these risks. The Russo-Ukrainian War is a clear example of a contemporary conflict illustrating these dynamics.

Until now, there is no study examining the connection of GPRs with SCTs. The majority of them focus on utility tokens such as transport, music, energy, and tourism. For instance, authors in [22] indicated that cryptocurrency volatility increases at high geopolitical levels. Similar findings were reported in [23-26] where GPR affected cryptocurrency returns and volatility.

B. Economic Uncertainty and SCT Nexus

The relationship between EPU and SCTs can be explained through monetary policy theories, liquidity preferences, and transaction costs. During periods of economic crisis, the traditional financial systems rely less on the cross-border payments and inventory management. SCTs, as digitally integrated trade assets, can mitigate the foreign currency fluctuations, expensive delays, while they can also resolve the liquidity imbalances. Additionally, heightened EPU encourages firms to enhance the eco-friendliness of their products and supply chain performance [27]. While research linking SCTs to EPU remains limited, authors in [14] revealed that SCT volatility increased during the economic crisis triggered by the COVID-19 pandemic.

C. Trade Uncertainty and SCT Nexus

The interaction of SCT and Trade Uncertainty Index (TUI) can be understood through the Principal-Agent Theory (PAT) [28]. Shifts in the trade policies, like new tariffs, trade regulations, and ESG restrictions expose firms to higher risks of non-compliance and regulatory penalties. The utilization of SCTs as new digital assets can improve their compliance and reinforce their monitoring standards. Thus, rising TUI is expected to develop the use of token-based systems to improve the supply chain operation efficiency [29, 30]. The impact of TUI on the supply chains has been investigated and it has been concluded that the sudden shifts in trade policy cause substantial disruptions in the supply chain operations [30-32]. The present study addresses these literature gaps by being the first to examine the effects of TUI, GPR, and EPU on the SCT market, particularly under extreme events.

III. DATA AND METHODOLOGY

A. Dataset

In this study, daily data obtained from the CoinMarketCap database were used for the highest capitalized SCTs: XYO, CXO, MNW, VET, and TRAC. The sample covered the period from 27th July 2018 to 5th March 2025, yielding 2,415 observations. The start date was determined by the availability of the SCT price data and token launch dates. This period faced extreme events, such as the COVID-19 outbreak, the Gaza-Israel conflict, and the ongoing Russo-Ukrainian war. The TUI, which was developed in [33], is based on automated text searches of seven newspapers. It is computed by counting the daily frequency of articles discussing TUI as a share of the total number of articles. The index is then normalized to 100 for a 1% share. EPU and GPR rely on the indexes constructed in [34].

B. The GJR-GARCH-DECO Model

To model the volatility and correlations, the GJR-GARCH model developed in [35] was utilized under the Dynamic Equicorrelations (DECO). It is a complex hybrid model accounting for stylized facts of financial time series, such as asymmetry, volatility clustering, and leverage effects [16, 17]. These aspects are critical when modeling financial assets' return and volatility, especially during the market downturns. Moreover, compared to a standard GJR-GARCH-CC or DCC, this type of model imposes an equicorrelation structure on intra-SCT connectedness, substantially reducing the complexity and overfitting risks. By the dynamic aspect of the equicorrelations, the intra-correlations among SCTs are visualized and the impact of the global risk factors during various market conditions can be assessed.

To estimate the DECO model, the univariate GARCH-class specification was firstly assessed. Specifically, the GJR-GARCH model was selected for the univariate step.

The SCTs' logarithmic return $r_{i,t}$ f of asset i at time t, is calculated by:

$$r_{i,t} = \rho r_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

$$h_{i,t}^2 = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1} + \gamma\varepsilon_{i.t-1} I_{t-1} \tag{2}$$

where $h_{i,t}^2$ denotes the conditional variance, α measures the impact of the lagged squared residual term on the actual conditional variance, β assesses the effect of the lagged conditional variance on its current value, and γ measures the asymmetrical impact of the positive and negative shocks (news) on the current volatility.

The conditional variance-covariance H_t matrix is given as:

$$H_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}} \tag{3}$$

where $R_t = [\rho_{(i,j,t)}]$ is the conditional correlation matrix between returns, and D_t designates the diagonal matrix of the conditional variances, which can be written as:

$$D_t = diag(h_{1,t}, h_{2,t}, \dots h_{n,t}) \tag{4}$$

Under the DCC specification [23]:

$$R_{t,DCC} = [Q_t^*]^{-1/2} Q_t\, [Q_t^*]^{-1/2} \tag{5(a)}$$

$$Q_t\ = (1-\psi-\xi)K + \psi\eta_{t-1}\eta'_{t-1} + \xi Q_{t-1} \tag{5(b)}$$

where ψ and ξ are non-negative scales verifying that $\psi + \xi < 1$. Q_t^* refers to the diagonal matrix combining the square root of the diagonal elements of the covariance matrix Q_t. In addition, $\eta_t = \varepsilon_{i,t}/h_{i,t}$ are standardized residuals and K is a $(n \times n)$ unconditional covariance matrix.

The conditional correlation between cryptos i and j at time t is:

$$\rho_{i,j,t} = \frac{q_{ij,t}}{\sqrt{q_{iit} q_{jj,t}}} \tag{6}$$

The conditional correlation matrix $R_{t,DCC}$ in the DECO formulation is:

$$R_{t,DCC} = (1-\rho_t) I_n + \rho_t J_n \tag{7}$$

where ρ_t is the equicorrelation at time t, while I_n and J_n refer to the dimensional identity matrix and the $(n \times n)$ matrix of ones, respectively.

The average DECO correlation is:

$$\rho_t^{DECO} = \frac{2}{n(n-1)} \sum_{i \neq j} \frac{q_{ij,t}}{\sqrt{q_{iit} q_{jj,t}}} \quad (8)$$

The DECO dynamics are given by [35]:

$$Q_t = (1 - \lambda - \pi)K + \lambda \, \eta_{t-1}\eta'_{t-1} + \pi \, Q_{t-1} \quad (9)$$

To ensure that the standard errors were robust, the DECO specification was estimated using the Quasi-Maximum Likelihood (QMLE) method [16].

IV. RESULTS AND DISCUSSION

A. Multivariate GJR-GARCH-DECO Results

Figure 1 illustrates the time-varying DECO of SCTs. The values presented considerable volatility, fluctuating between 0.3 and 0.8, with several sharp increases matching with extreme events. The first peak occurred at the end of 2018, aligning with the bans imposed on cryptocurrencies from both China and India. The highest peak was observed in 2020, corresponding to the COVID-19 health crisis and the simultaneous oil market shock. Another notable rise was detected in 2022, which is associated with the Russo-Ukrainian war. This trend indicated that SCTs are closely interconnected during significant market disruptions, where their ability to generate diversification profits was diminished. This finding is similar with that of prior studies dealing with traditional cryptocurrencies [11, 15-17, 24].

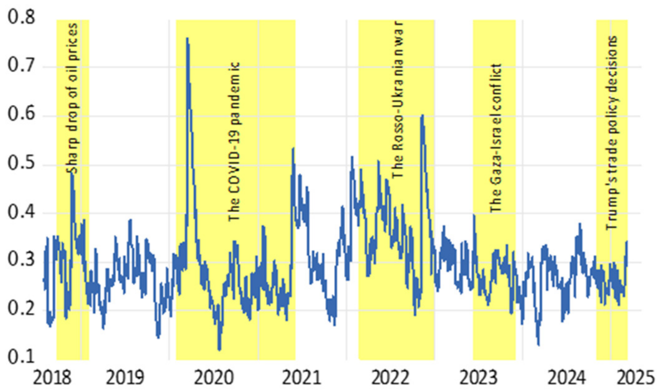

Fig. 1. The SCTs' time-varying DECO.

Table I presents the estimation results from GJR-GARCH-DECO model. From panel A, the estimated coefficients α and β were significant, indicating that SCTs were strongly affected by past volatility shocks. The leverage effect parameter was also important, showing the presence of asymmetries and leverage effects. These trends were associated with the results for gold-backed cryptocurrencies [16], though differed from the traditional ones [17]. The diagnostic tests (Panel B) revealed that the selected univariate specification met all the required tests. The Ljung-Box tests of standard squared residuals did not reject the null hypothesis of no serial correlations. In contrast, the ARCH tests rejected the homoscedasticity null hypothesis, confirming the specification's suitability.

When looking at the estimated DECO (Panel C), the average correlation was relatively weak but positive (0.27) and statistically significant. This may indicate a relatively low degree of the SCTs' market integration and reveal driven by common influences, such as trader sentiment, regulatory shifts, global risk factors, and extreme events. The time-varying nature of DECO was more relevant to understanding how their dependence varied over time. The parameter γ was statistically meaningful, showing that the SCT correlations were affected by shocks. The estimated coefficient π was major at 1%, implying that the DECOs exhibited a relatively high persistence over time and a relatively slow mean-reverting process. The multivariate diagnostic tests (Panel D) confirmed the suitability of the model, where both the Li-McLeod and Hosking tests failed to reject the null hypothesis of no serial correlations.

TABLE I. THE GJR-GARCH-DECO RESULTS

Parameters	**VET**	**MNW**	**XYO**	**TRAC**	**CXO**
Panel A: coefficient estimates					
ρ	-0.03* (-1.78)	-0.050* (-1.61)	-0.150* (-3.98)	-0.08*** (-3.18)	-0.25*** (-9.52)
ω	1.08** (1.68)	0.21 (1.09)	3.31 (1.27)	0.45 (1.02)	0.70 (1.34)
α	0.13*** (3.01)	0.002*** (3.02)	0.206** (2.30)	0.30** (1.96)	0.117** (2.24)
β	0.83*** (14.19)	0.94*** (55.05)	0.79*** (9.75)	0.93*** (28.43)	0.87*** (20.55)
γ	0.02*** (3.21)	0.146* (1.69)	0.01** (2.32)	0.01** (2.40)	0.04** (2.25)
Panel B: univariate diagnostic tests					
Q^2 (20)	9.60 [0.97]	0.013 [0.99]	9.37 [0.97]	14.70 [0.79]	2.47 [0.77]
Arch (10)	0.245 [0.92]	0.351 [0.96]	0.186 [0.99]	0.431 [0.92]	0.132 [0.99]
Panel C: multivariate DECO model estimations					
ρ_{DECO}	0.27*** (2.68)				
γ	0. (1.65)				
π	0.06*** (13.57)				
Panel D: multivariate diagnostics					
Hosking (20)	180.60 [0.999]				
Li-McLeod (20)	537.81 [0.999]				

Parentheses: The standard errors related to each coefficient.
Brackets: The probabilities which were corrected by 2 degrees of freedom.
(*), (**), (***): the significance at the 10%, 5%, and 1% levels.
Q^2(20): The Ljung-Box test for squared residuals.
ARCH(10): The LM ARCH test for up to 10th lags.

B. Drivers of SCT Equicorrelations and Extreme Events

The DECO mean and variance equations are written as:

$$DECO_t = \beta_0 DECO_{t-1} + \beta_1 EPUI_t + \beta_2 EPUI_{t-1} + \beta_3 TUI_t + \beta_4 TUI_{t-1} + \beta_4 GPR_t + \beta_4 GPR_{t-1} + e_{i,t} \quad (10)$$

$$h_{ij,t} = c + a e_{ij,t}^2 + b h_{ij,t} + \sum_{k=1}^{m} d_k \, dum_{k,t} \quad (11)$$

where $DECO_t$ refers to the equicorrelations at time t and $dum_{k,t}$ denoted a dummy variable indicating the turbulent period. The DCCs were expressed in their logarithmic changes when incorporated as the dependent variable of the GARCH mean equation. The estimation results are displayed in Table II.

TABLE II. THE AUGMENTED GARCH MODEL FOR THE DECO

	Model 1	Model 2
Panel A: The mean: $DECOC_t = \beta_0 DECOC_{t-1} + \beta_1 EPUI_t + \beta_2 EPUI_{t-1} + \beta_3 TPUI_t + \beta_4 TUI_{t-1} + \beta_5 GPR_t + \beta_6 GPR_{t-1} + e_{i,t}$		
β_0	0.984*** (48.37)	0.983*** (80.15)
β_1	0.001 (0.15)	-
β_2	0.001 (0.78)	-
β_3	0.002 (0.32)	-
β_4	0.001 (0.44)	-
β_5	0.031*** (4.10)	0.027** (2.05)
β_6	0.025** (3.22)	0.015* (1.65)
Panel B: The conditional variance: $h_{ij,t} = c + ae_{ij,t}^2 + bh_{ij,t} + \sum_{k=1}^{m} d_k\, dum_{k,t}$		
C_{st}	1.07*** (13.9)	0.0002*** (10.31)
a	0.07*** (10.55)	0.057*** (11.54)
b	0.69*** (31.39)	0.5819*** (17.56)
$dum_1(hacking - Blokchain)$	-	-0.001*** (-8.21)
$dum_2(Covid - 19)$	-	-0.0007*** (-7.25)
$dum_3(Ukrain\ war)$	-	-0.0009*** (-8.22)
$dum_4(Gaza - Israel\ Conflict)$	-	-0.006*** (-7.91)
$dum_5(Trump)$	-	-0.001*** (-5.91)
$LB(20)$	10.22 [0.99]	9.65 [0.98]

Values reported between parentheses are the t-students.

$LB(20)$ is the Ljung-box statistic for the 20th squared residuals while values between brackets are the corresponding p-values.

The descriptive statistics of the logarithmic return and daily changes of the global risk factors revealed their stationarity, presence of ARCH effects, fat-tailed and skewed returns, and significant deviations from normal distributions. These properties confirmed that the supply chain cryptocurrencies were suitable for a GARCH-class modeling. Due to space scarcity, these statistics are not reported but are available upon request. In Model 1, three risk factors (EPU, TUI, and GPR) were included in the DECO conditional mean equation. Unit root tests indicated that the series were stationary in the first level, so their first differences were used. The results showed that only the current and lagged GPR variables were noteworthy. A further version of Model 1, which included the current and lagged values of all three risk factors, estimated insignificant coefficients, suggesting no influence of DECO volatility. The positive signs of the GPR parameters demonstrated that higher GPR levels strengthened the SCT co-movements. In Model 2, five dummy variables - blockchain hacking incidents (May 2018), COVID-19 pandemic (March 2020), the Russo-Ukrainian war and the related energy crisis in Europe (February 2022), Gaza-Israel conflict (October 2023), and the recent Trump' trade policy decisions (November 2024) - were included representing some extreme events into the DECO conditional variance equation in order to examine whether and how these events could affect the SCT co-movements. From the conditional mean equation, GPR and its lagged values significantly improved the SCT equicorrelations. In contrast, all extreme events decreased the volatility of the equicorrelations. The Granger causality tests were performed to check whether EPU, GPR, and TUI cause the SCT market equicorrelations. The pairwise causality test results are reported in Table III. It was confirmed that EPU and TUI did not Granger-caused SCT equicorrelations, while GPR did. The null hypothesis that GPR does not cause DECO was rejected, supporting the prior results regarding the impact of global risk factors on the strength of the SCT equicorrelations.

TABLE III. THE PAIRWISE CAUSALITY TEST RESULTS

Null hypothesis	*F*-Statistics
EPU does not cause SCTs' DECO	1.15 (0.31)
SCTs' DECO does not cause EPU	0.99 (0.37)
GPR does not cause SCTs' DECO	3.54** (0.02)
SCTs' DECO does not cause GPR	1.93 (0.14)
TUI does not cause SCTs' DECO	0.62 (0.53)
SCTs' DECO does not cause TUI	1.13 (0.32)

The *p*-values are reported in parentheses.

V. CONCLUSION

This study investigated the influence of Economic Policy Uncertainty (EPU), Trade Uncertainty Index (TUI), and Geopolitical Risks (GPR) on the time-varying intra-market connectedness of Supply Chain Tokens (SCTs). The multivariate GJR-GARCH model was implemented under Dynamic Equicorrelations (DECO) assumptions for five SCTs from 2018 to 2025.

The results yielded several insights:

- SCT correlations were highly volatile, with values ranging between 0.3 and 0.8.
- Extreme events, such as the COVID-19 and geopolitical tension periods, exhibited high correlation levels. Reaching a peak of 0.8 during the health crisis.
- The GPR exhibited a positive impact on the SCT time-varying correlations implying higher levels of market integration during episodes of geopolitical tensions.
- EPU and TUI had no impact.
- Extreme events significantly decreased the supply chain correlations' levels.

Future research could extend this analysis to other token categories and explore alternative methods, such as wavelet-based approaches, to capture time–frequency dynamics under global uncertainty,

ACKNOWLEDGMENT

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2504).

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