

Geopolitical Risk and Global Financial Market Connectedness: Evidence from TVP-VAR Spillovers and DCC-GARCH Correlations

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Abstract

This study analyses the dynamic spillover transmission and time varying correlation structure between geopolitical risk and major financial markets around the world from January 2005 to March 2026. The analysis builds a multi-asset framework that includes developed and emerging equity markets, commodities, exchange rates and market volatility to reflect the overall architecture of financial interconnections in the world. In terms of methodology, the study uses a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to estimate the direction of the spillover effects, and the Dynamic Conditional Correlation GARCH (DCC-GARCH) model to evaluate the time-varying market co-movements and diversification dynamics. The results indicate that the global financial markets are deeply interconnected, and that most of the developed equity markets tend to be net transmitters of shocks, whereas the emerging markets, commodities and exchange rates are net receivers. Total connectedness is very volatile, and it surges significantly during systemic crisis periods, such as the Global Financial Crisis and the COVID-19 pandemic. The VIX is identified as an important transmission path of uncertainty, reflecting the role of global risk sentiment in the transmission of uncertainty across markets. The average spillover impact of geopolitical risk is modest, and it is more important during times of geopolitical uncertainty, indicating a non-linear and episodic effect. The DCC-GARCH results also show that the correlation between markets increase during crises, thereby limiting the effectiveness of international diversification. Lastly, the study reveals that geopolitical risk has a selective and regime specific impact on global financial markets and that the use of dynamic modelling is necessary to grasp the connections, linkages and diversification risks within an increasingly integrated financial system.

Keywords; Geopolitical risk; Financial connectedness; TVP-VAR; DCC-GARCH; Dynamic spillovers; VIX; Global financial markets; Diversification

1.Introduction

The growing integration of global financial markets has significantly altered the nature and transmission of economic and financial shocks across countries and asset classes (Donadelli *et al.*, 2024). Advances in financial liberalization, technological innovation, and cross-border capital mobility have strengthened linkages among equity markets, commodities, exchange rates, and volatility indices (Wang, 2022). Although this type of interconnectedness leads to higher market efficiency, it also makes financial systems more prone to contagion, especially in times of crisis (Cevik *et al.*, 2024). Consequently, the dissection and development of spillovers in international markets have been an important issue in financial economics. A huge amount of literature has been dedicated to the measurement and analysis of financial market connectedness. The model designed by Diebold, (2015) is a popular method of measuring spillovers through forecast error variance decompositions. Antonakakis *et al.*, (2020) have extended this methodology by introducing Time-Varying Parameter Vector Autoregression (TVP-VAR) model that enables more flexible representation of dynamic relationships without the use of rolling window estimation. Simultaneously, Dynamic Conditional Correlation (DCC-GARCH) model introduced by Engle, (2002) has become a common instrument to analyse time-varying correlations between financial assets. Such methodological innovations have helped researchers to both describe the direction of interconnectedness and its strength as it changes over time.

Meanwhile, more emphasis has been put on geopolitical risk as a factor affecting financial markets. Geopolitical risk index is a systematic indicator of geopolitical tensions using news-based indicators (Caldara and Iacoviello, 2022). Existing studies suggest that geopolitical events, such as wars, political instability, and international conflicts can affect market volatility, asset returns, and investor sentiment (Aslam and Newaz, 2025). Nevertheless, the effects of geopolitical risk are typically nonlinear and time-dependent, and the interaction between geopolitical risk and the general financial market dynamics are less well understood (Gheorghe and Panazan, 2025). Even though the subject of financial connectedness has received a substantial amount of literature and geopolitical risk has become a topic of increased interest, there remains a significant gap. Most of the research is likely to investigate such features separately, either the relationships of spillovers between the financial markets or the impact of the geopolitical risk on the specific asset classes.

Additionally, the number of studies that combine systemic spillover measures and time-varying correlation structure into one empirical framework is relatively small (Li *et al.*, 2023). This is constraining about the capability of fully modelling the multifaceted and changing relationships amid global financial markets and geopolitical uncertainty, especially among the various economic regimes. In this regard, the current research examines the dynamic spillover and correlation framework of key international financial markets and geopolitical risk during the January 2005-March 2026 timeframe. This time includes several significant world events such as Global Financial Crisis, European Debt Crisis, the COVID-19 pandemic and the most recent geopolitical conflicts, all of which have had substantial impact on market behaviour and interdependence. To tackle the research aim, the study uses a rich empirical framework that is a combination of initial statistical diagnostics and a TVP-VAR connectedness model and a DCC-GARCH model. The time-varying bilateral correlations are analysed through the DCC-GARCH model and the dynamic transmission of shocks and the development of total and directional connectedness between variables are captured with the help of the TVP-VAR framework. A combination of these methods can be used to obtain a more comprehensive description of the systemic and pairwise interactions and have a more detailed perspective of dynamics in global financial interconnectedness under conditions of geopolitical risk.

2. Literature Review

Global financial market spillovers have moved from early discussions on market integration and contagion to more advanced models of dynamic connectedness, time-varying correlations and geopolitical risk transmission in the literature. Financial integration increases investment opportunities, better capital allocation and enhanced international risk sharing, but also raises the risk that shocks in one market or asset class can be quickly passed to other markets. The dual aspect of integration is a central theme of the study of dynamic spillovers, as periods of stability can lead to diversification benefits, while crisis and uncertainty regimes tend to increase the correlations, volatility transmission and decrease portfolio protection. (Antonakakis *et al.*, 2020; Diebold and Yilmaz, 2012; Donadelli *et al.*, 2024).

2.1 Financial Market Integration, Contagion, and Cross-Market Spillovers

Financial market integration is the growing entanglement of cross-country movements of capital, asset prices and risk premia. While global financial integration has grown over time, the impact has been disputed due to the use of various definitions, measures, samples and econometric techniques in the studies, according to Donadelli et al., (2024). While integration can enhance diversification and capital allocation, it can also increase the shock's transmission and decrease the diversification benefits during crises. Recently, however, literature on integration has tended to see integration as a process, rather than a state of being. The term "cross-market spillovers" is used to describe the channel of observations of integration, because shocks to one market have impacts on returns or volatility in other markets. The formalization of this by Diebold & Yilmaz, (2012) allows to measure net and total spillovers between countries and markets, as well as the identification of net transmitters and receivers, across the global financial markets. Empirical work indicates that financial spillovers are dynamic and tend to be more significant in times of crises. Before the Global Financial Crisis, volatility spillovers between U.S. stocks, bonds, foreign exchange and commodities were not substantial, but they increased dramatically after the Lehman Brothers failure, Diebold & Yilmaz, (2012) report. Likewise, Cevik et al., (2024) report that the systemic risk positions of developed stock markets were more important before the crisis, and China and India were more important after the crisis, suggesting a shift in systemic risk from the West to the East. This is supported by commodity and regional studies, as well. According to AlGhazali et al., (2025), oil volatility and global risk factors have an impact on the markets of the Gulf Cooperation Council. Baur & Lucey, (2010) demonstrate that gold offers short-term safe-haven effects when markets are severely stressed.

2.2 Time-Varying Connectedness and Dynamic Correlation Modelling

One of the main ways to measure financial spillovers is based on the Diebold & Yilmaz, (2012) connectedness framework. It applies forecast-error variance decompositions from generalized VAR models to demonstrate the causal impact of shocks between different markets. This method permits to estimate the total spillover, the directional spillover, the net spillover and the pairwise spillover without relying on ordering variables. It is based on Pesaran & Shin, (1998) generalized impulse response analysis without shock orthogonalization.

Antonakakis et al., (2020) then generalize this approach by incorporating a time-varying parameter and time-varying covariance structure (TVP-VAR) without making any assumptions about the way the parameters or the covariance structure should roll. Previous spillover analyses relied on static or rolling window models, the latter of which inevitably involves specifying an arbitrarily long window, either to react to short-lived shocks or to filter out larger changes. Antonakakis et al., (2020) demonstrate that TVP-VAR connectedness indices are more sensitive to economic events and offer more flexible estimates of dynamic spillovers. This is important because financial spillovers are different under different regime of normal, crisis and uncertainty. Aslam & Newaz, (2025), also demonstrate that geopolitical risk plays a significant role in the bond-market-connectedness during key events. Therefore TVP-VAR can be used for the analysis of net transmitters and receivers in the evolving geopolitical scenario.

2.3 Geopolitical Risk, Volatility Transmission, and Multi-Asset Market Responses

Geopolitical risk is now a key driver of financial market actions around the world. It impacts markets in several ways: uncertainty of the future cash flows, risk premium adjustments, flight to safety behaviour, commodity supply disruptions, exchange rate expectations and investor sentiment. Aslam & Newaz (2025), suggest that geopolitical events like wars, terrorist attacks, diplomatic tensions, U.S.-China trade wars, COVID-19, the Russia-Ukraine war, and Middle East tensions impact investor behavior, risk premia, and asset pricing. The most dominant measure in the literature reviewed is the Geopolitical Risk Index, by Caldara & Iacoviello, (2022), which quantifies war, conflict, terror, military escalation, nuclear threat, sanctions and geopolitical tensions by counting articles automatically retrieved from newspapers and normalizing them by the total number of articles in the newspaper. It includes news from both the past and the present starting from 1900, and tracks high-frequency geopolitical uncertainty, not just actual events. Its major contributions are distinguishing threats from acts, and distinguishing between threats and acts. This enables the analysis of GPR, GPR_ACT and GPR_THREAT individually, to understand how expected tensions and actual events can impact bond markets in different ways, with varying timing, duration and pathway. Geopolitical risk is a major driver of equity markets, as stock prices reflect expectations of earnings, discount rates, risk appetite and macroeconomic stability. In times of uncertainty, investors tend to pull back on purchasing equities, shift into defensive industries and/or invest in safe-haven assets which can lead to volatility and spillovers. There is also evidence

from recent studies of sector-specific effects. Gheorghe & Panazan, (2025) conclude that there are nonlinear relationships between geopolitical uncertainty and volatility, with defensive industries such as defence and cyber security being shock insensitive, and shock sensitive industries such as energy and raw materials.

2.4 Crisis Regimes, Correlation Breakdowns, and Diversification Limits

A consistent finding from the literature is that diversification gains are reduced during times of crisis due to increases in correlations and spillovers at the exact moment that diversification is most needed. This phenomenon occurs in equity markets, commodity markets, bond markets, and multi-asset portfolios. Longin & Solnik, (2001) demonstrate that the correlation tends to rise during bear markets, whereas Forbes & Rigobon, (2002) warn that it is important to take care with interpretations of correlation increases during the crisis periods as volatility might lead to mechanical bias in correlation estimates. Dynamic models, therefore, are crucial to the study of diversification. Normal period estimates of static correlation may overestimate integration or underestimate contagion during a crisis. However, DCC-GARCH and TVP-VAR models overcome this limitation by making it possible to have varying correlations and spillovers according to market conditions.

2.5 Research Gaps and Contribution of the Present Study / Justification of the Study

There are several important gaps in the literature reviewed. Second, many studies focus on spillovers within a single asset class (e.g., in equity, bond, commodity, or exchange rate) while far fewer studies investigate the spillover and correlation dynamics simultaneously in multiple global financial markets. This is a major constraint as geopolitical risk has a cross-market nature: it can impact equities via earnings expectations, bonds via flight-to-safety behaviour, commodities via supply shocks and currencies via capital flows and current-account expectations. Second, the Diebold and Yilmaz, (2012) and TVP-VAR connectedness frameworks provide useful instruments to determine the presence of directional spillovers but are not directly measuring dynamic correlations and diversification effectiveness. In contrast, DCC-GARCH models can analyze time-varying correlation, but cannot detect directional transmission of shocks. A TVP-VAR approach together with a DCC-GARCH approach can thus give a more comprehensive empirical framework that can combine spillover direction with dynamic co-movement.

Third, geopolitical risk is often considered as a single aggregated value. But the literature is now beginning to suggest that there could be different impacts between geopolitical threats and realized geopolitical acts. Aslam & Newaz, (2025) demonstrate that threat-related risks may be more enduring than realized events in bond markets, and Caldara and Iacoviello's framework offers a measure for distinguishing between different geopolitical risks.

Also, diversification in the context of geopolitical risk is not sufficiently well understood. Gold could be a temporary safe haven, bonds may not be effective at all times, volatility in oil stocks can be a factor, and emerging equity markets can become systemic during different regimes. These results indicate that portfolio diversification is not a universal, but rather a conditional strategy and it also shows that the effectiveness of portfolio diversification depends on the prevailing spillover and correlation structure.

Therefore, the present study is justified both in terms of methodological and empirical aspects. From a methodological point of view, it can help by embedding the connectedness of TVP-VAR with DCC-GARCH correlation analysis, which can measure spillovers and time-varying co-movement. Empirically, it could help by analysing the global financial markets in the context of geopolitical risks, separating normal from crisis and conflict regimes, and determining which markets are net transmitters, net receivers, a hedge or safe haven. This kind of analysis can offer valuable insights to investors, policy makers, and risk managers interested in the implications of geopolitical uncertainty for the interdependence of global financial markets

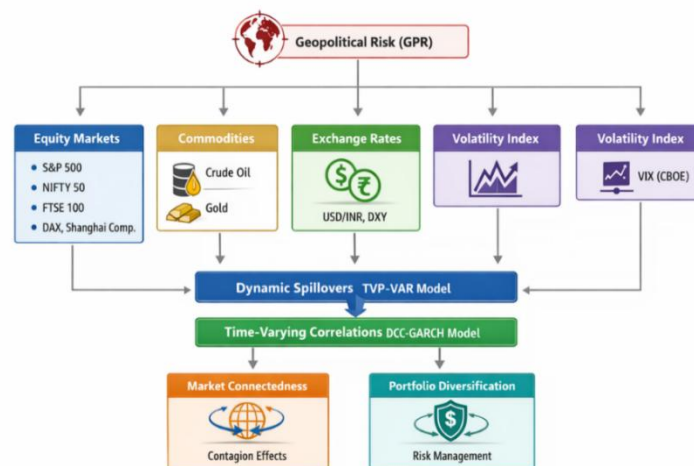


Figure 1 Conceptual Framework

3. Research Methodology

This study investigates the dynamic spillover and time-varying correlation structure among ten global financial market variables and geopolitical risk over the period January 2005 to March 2026. The methodological architecture will be able to not only reflect a systemic transmission of shocks between markets but also reflect bilateral co-movement patterns that change depending on macroeconomic and geopolitical regimes. The empirical framework incorporates three layers which are complementary and include: (i) initial statistical diagnostics, (ii) Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness framework in the tradition of Diebold, (2015), Antonakakis *et al.*, (2020) and (iii) Dynamic Conditional Correlation GARCH (DCC-GARCH) proposal introduced by (Engle, 2002).

3.1 Data Description and Sample Construction

The empirical part is based on ten variables: the S&P 500 (USA), NIFTY 50 (India), FTSE 100 (United Kingdom), DAX 30 (Germany), Shanghai Composite (China), Brent Crude Oil prices, Gold Spot prices (USD/oz), the US Dollar Index (DXY) as a proxy of exchange rate dynamics, the CBOE Bloomberg, the U.S. Energy Information Administration (EIA), the Federal reserve economy data (FRED), and the Caldara and Iacoviello, (2022) GPR database, respectively are the sources of these variables. The sample period includes five major systemic events, including the Global Financial Crisis (GFC, 20052009), the European Debt Crisis (EDC, 20102015), the pre-COVID Stability period (20162019), the COVID-19 Pandemic (20202021), and the Russia-Ukraine War and high geopolitics. This periodisation makes it possible to compare intensity and correlation dynamics of spillovers on a regime sensitive basis. **Table 1** summarises the variable definitions, proxies, and data sources.

Table 1: Variable Definitions, Proxies, and Data Sources

Variable	Proxy / Index	Description	Frequency	Period	Source
Geopolitical Risk	GPR Index	Measures geopolitical tensions (wars, terrorism, conflicts)	Daily	2005–2026	Caldara & Iacoviello DB
US Market	S&P 500	Benchmark index for US equity market	Daily	2005–2026	Bloomberg

Indian Market	NIFTY 50	Benchmark index for Indian equity market	Daily	2005–2026	Bloomberg
UK Market	FTSE 100	UK blue-chip stock market index	Daily	2005–2026	Bloomberg
Germany Market	DAX 30	German prime standard stock index	Daily	2005–2026	Bloomberg
China Market	Shanghai Composite	Chinese equity market benchmark	Daily	2005–2026	Bloomberg
Crude Oil	Brent Crude	Global oil price benchmark	Daily	2005–2026	U.S. EIA
Gold	Gold Spot (USD/oz)	International safe-haven asset price	Daily	2005–2026	World Gold Council
Exchange Rate	USD Index (DXY)	Captures broad currency dynamics	Daily	2005–2026	RBI
Volatility Index	VIX (CBOE)	Proxy for global financial uncertainty	Daily	2005–2026	CBOE

All price-level series are converted into continuously compounded logarithmic returns to ensure stationarity and comparability across series of differing scales, defined as:

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

The dataset is aligned to common trading days across markets, and non-synchronous trading gaps are addressed through standard data-cleaning protocols. The GPR Index is used in its level form, consistent with the practice of Caldara and Iacoviello, (2022), as it represents a standardised textual measure of geopolitical risk rather than a financial price series.

3.2 Preliminary Statistical Analysis

A series of initial diagnostics are performed before model estimation. The descriptive statistics, such as mean, standard deviation, skewness, excess kurtosis, Jarque-Bra test, are calculated to describe the distributions of each of the return series. Data on financial returns generally has excess kurtosis and negative skewness which are indicative of fat-tailed distributions and asymmetric loss behaviour, which are consistent with the stylised facts reported in (Cont, 2001). The null hypothesis of stationarity of all the return series is formally tested by both the Augmented Dickey-Fuller (ADF) test and Philips-Perron (PP) test which both assume the null hypothesis of a unit root. The best lag length of the VAR system is determined through Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) which allows consideration

of parsimony against model fit. The unconditional Pearson correlation matrix is also given to describe the unconditional linear relationships among the variables prior to dynamic modelling.

3.3 Time-Varying Parameter VAR (TVP-VAR) Connectedness Framework

3.3.1 Model Specification

This research paper uses the TVP-VAR-based connectedness model of Antonakakis *et al.*, (2020) which builds upon the seminal Diebold and Yilmaz, (2014) model, by letting the covariance of the error, as well as the coefficients of the VAR, to vary over time. This method does not rely on arbitrarily selecting the rolling-window width which is a known weakness of the original connectedness methodology and allows structure breaks and regime shifts inherent in financial time series to occur. The model is TVP- VAR (p) as:

$$Y_t = A_{1,t}Y_{t-1} + A_{2,t}Y_{t-2} + \dots + A_{p,t}Y_{t-p} + \varepsilon_t$$

where Y_t is a vector of endogenous variables, $A_{\{i,t\}}$ represents time-varying coefficient matrices, and ε_t is a vector of error terms with time-varying covariance matrix. The change of parameters is randomly walked:

$$A_t = A_{t-1} + u_t$$

This framework is estimated using the **Kalman filter** approach.

3.3.2 Generalised Forecast Error Variance Decomposition

The measures of connectedness are based on the H-step-ahead Generalised Forecast Error Variance Decomposition (GFEVD) as in Koop *et al.*, (1996) and Pesaran and Shin, (1998). The GFEVD is invariant to the ordering of variables (unlike Cholesky-based decompositions), so it is especially useful in a multi-market system where a natural recursive causal ordering is absent. The pairwise GFEVD entry $\psi_{ij}(H)$ is the fraction of the variance of the H-step-ahead forecast error of variable i that can be attributed to shocks that originated in variable j:

$$\psi_{ij}(H) = (\Sigma^{-1}_{jj} \Sigma^h_{\{h=0\}^{H-1}} (e'_i \Phi_h \Sigma e_j)^2) / (\Sigma^h_{\{h=0\}^{H-1}} e'_i \Phi_h \Sigma \Phi'_h e_i)$$

where Φ_h is the impulse-response coefficient matrix at horizon h, Σ is the covariance matrix, and e_i is a selection vector with unity in position i and zeros elsewhere. The GFEVD is row-normalised to sum to unity.

3.4 Dynamic Connectedness Framework

To quantify spillovers, the study adopts the Diebold and Yilmaz, (2014) connectedness approach based on Generalized Forecast Error Variance Decomposition (GFEVD). The key measures include:

- Total Connectedness Index (TCI): Captures overall system-wide spillovers
- Directional Spillovers: Measures spillovers transmitted to and from each variable
- Net Spillovers: Difference between transmitted and received spillovers

These measures are computed dynamically using the TVP-VAR framework, allowing the analysis of how connectedness evolves over time, particularly during crisis periods such as the Global Financial Crisis, COVID-19 pandemic, and recent geopolitical conflicts.

3.5 DCC-GARCH Model

To complement the spillover analysis, the study employs the **Dynamic Conditional Correlation (DCC-GARCH)** model proposed by Engle, (2002) to estimate time-varying correlations among the variables. In the first stage, a univariate GARCH (1,1) model is estimated for each return series:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

In the second stage, the conditional correlation matrix is modeled as:

$$H_t = D_t R_t D_t$$

where D_t is a diagonal matrix of conditional standard deviations and R_t is the time-varying correlation matrix. The dynamic correlation process is defined as:

$$Q_t = (1 - a - b)\bar{Q} + a(\epsilon_{t-1}\epsilon'_{t-1}) + bQ_{t-1}$$

This model enables the identification of **time-varying co-movement patterns** and the strength of correlations across markets under different economic conditions.

3.5 Sub-Period Analysis

To assess the sensitivity of connectedness and correlation dynamics to distinct macroeconomic and geopolitical regimes, both the TVP-VAR and DCC-GARCH estimates are summarised across five pre-defined sub-periods. This regime-based decomposition is grounded in the identification strategy of Forbes and Rigobon, (2002) and allows for the formal assessment of

crisis-contingent amplification in spillovers and correlations. The five sub-periods and their rationale are defined in **Table 2**.

Table 2 : Sub-Period Classification and Rationale

Sub-Period	Event	Rationale
2005–2009	Global Financial Crisis (GFC)	Onset of the subprime mortgage collapse and subsequent global banking crisis. Represents a systemic shock of unprecedented peacetime severity.
2010–2015	European Debt Crisis (EDC)	Sovereign debt distress in the Eurozone periphery, contagion to European banking systems, and ECB unconventional monetary policy interventions.
2016–2019	Pre-COVID Stability	Relative macroeconomic stability with moderate geopolitical risk, serving as the baseline for comparing crisis-period connectedness.
2020–2021	COVID-19 Pandemic	Global synchronised demand shock driven by pandemic lockdowns, unprecedented fiscal and monetary stimulus, and extreme volatility across all asset classes.
2022–2026	Russia–Ukraine War & Elevated GPR	Escalation of geopolitical risk, energy market disruptions, inflationary pressures, and aggressive global monetary tightening.

3.6. Hypothesis Development

The hypotheses of this study are developed based on established theoretical and empirical literature, as presented in **Table 3** . Prior studies highlight the role of geopolitical risk in influencing financial markets, the time-varying nature of connectedness, and the asymmetric transmission of shocks across developed and emerging markets. Additionally, existing evidence on safe-haven assets, volatility transmission, and dynamic correlations supports the formulation of hypotheses related to gold, VIX, commodities, and exchange rates, providing a structured basis for empirical analysis.

Table 3 : Hypothesis Development

Hypothesis	Statement	Key Supporting Studies
H1	Geopolitical risk significantly influences spillover dynamics among global financial markets.	(Bouri <i>et al.</i> , 2019; Caldara and Iacoviello, 2022)
H2	The connectedness among global financial markets is time-varying and intensifies during crisis periods.	(Antonakakis <i>et al.</i> , 2020; Diebold and Yilmaz, 2012)

H3	Developed markets act as net transmitters, while emerging markets act as net receivers of shocks.	(Bekaert <i>et al.</i> , 2005; Forbes and Rigobon, 2002)
H4	Gold acts as a safe-haven asset during periods of high geopolitical risk.	(Baur and Lucey, 2010)
H5	The volatility index (VIX) acts as a major transmitter of shocks to global markets.	(Whaley Robert, 2000)
H6	Dynamic correlations among global financial markets increase during crisis periods.	(Engle, 2002; Longin and Solnik, 2001)
H7	Commodity markets exhibit significant time-varying linkages with equity markets under geopolitical stress.	(AlGhazali <i>et al.</i> , 2025)
H8	Exchange rate movements significantly affect cross-market spillovers and correlations.	(Dornbusch and Fischer, 1980; Phylaktis and Ravazzolo, 2005)

4. Data Analysis and Interpretation

This section gives a structured presentation and interpretation of the empirical results. The first part of Section 4.1 covers the initial statistical diagnostics, such as descriptive, the result of the stationarity test, and the result of the static correlation matrix. The complete-system TVP-VAR connectedness findings including the Total Connectedness Index and directional net spillovers are in Section 4.2. Section 4.3 examines the DCC-GARCH-generated dynamic correlations of important market pairs. In Section 4.4, the connectedness and correlation are further broken down into sub-periods, which are consistent with the key global events that were found in the previous section (3.5).

4.1 Preliminary Diagnostics

4.1.1 Descriptive Statistics

Figure 2 shows the time series of logarithmic returns of all ten variables throughout the entire sample period. The return plots demonstrate various characteristic aspects of financial time series, such as volatility clustering, extreme events at times and regime heteroscedasticity.

Particularly, the time of the GFC (2007-2009), the COVID-19 shock (2020), and, to a smaller degree, the period of the Russia-Ukraine War (2022) can be singled out as the periods of increased volatility of equity markets (S&P 500, NIFTY 50, FTSE, DAX) and commodity markets. It can be seen that gold and the exchange rate exhibit a relatively less pronounced volatility in the returns, which is in line with their usage as defensive or safe-havens. The distribution of the GPR series is not that of financial return series but rather level-based with sustained higher values when geopolitical stresses occur.

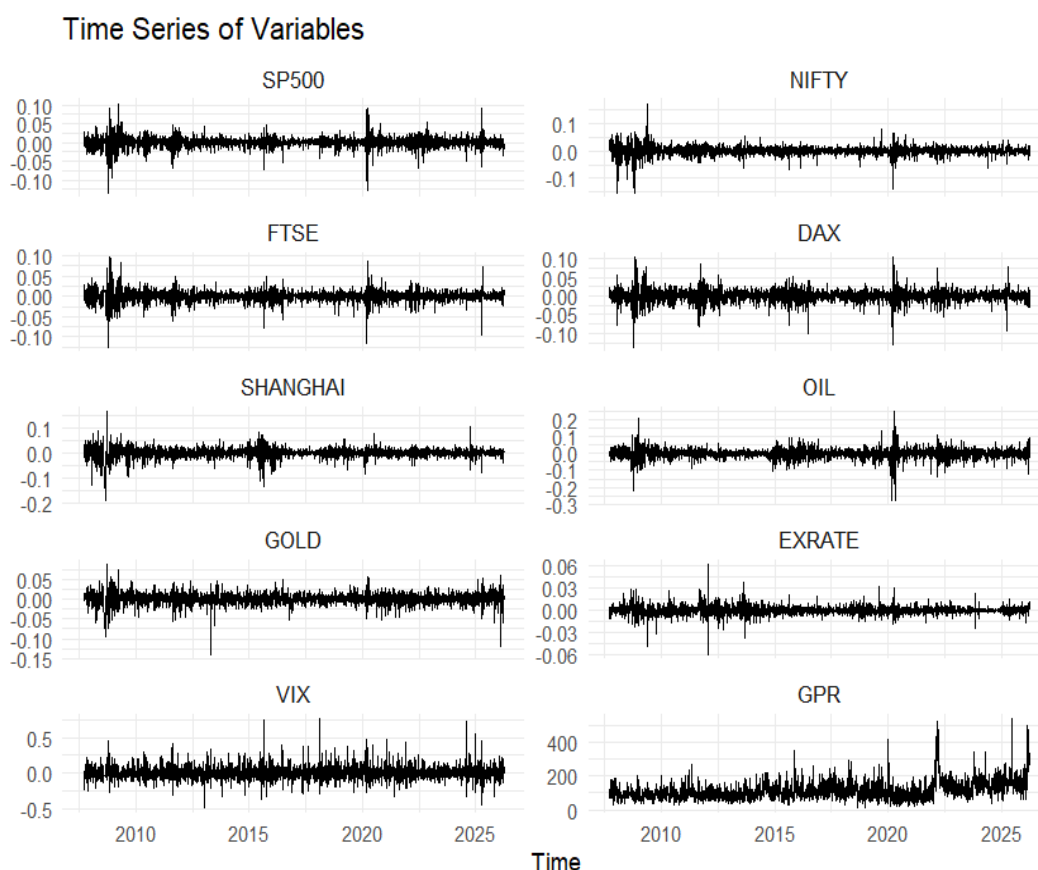


Figure 2 : Time Series of Logarithmic Returns — All Variables (January 2005 – March 2026)

Table 4 reports the ADF unit root test results for all ten-return series. All series reject the null hypothesis of a unit root at the 1% significance level ($p < 0.01$), confirming that the logarithmic return transformation achieves stationarity across the board. This is a prerequisite for valid inference within both the VAR and GARCH frameworks employed in this study.

Table 4 : Augmented Dickey-Fuller (ADF) Unit Root Test Results

Variable	ADF Test Statistic (p-value)	Decision (1% Level)
SP500	< 0.01	Reject H_0 — Stationary
NIFTY 50	< 0.01	Reject H_0 — Stationary
FTSE 100	< 0.01	Reject H_0 — Stationary
DAX	< 0.01	Reject H_0 — Stationary
Shanghai Composite	< 0.01	Reject H_0 — Stationary
Brent Oil	< 0.01	Reject H_0 — Stationary
Gold	< 0.01	Reject H_0 — Stationary
USD Index (DXY)	< 0.01	Reject H_0 — Stationary
VIX	< 0.01	Reject H_0 — Stationary
GPR Index	< 0.01	Reject H_0 — Stationary

Note: H_0 denotes the null hypothesis of a unit root. All series are tested in logarithmic return form. The 1% critical values for the ADF test are applied throughout.

4.1.2 Static Pearson Correlation Matrix

Table 5 shows the Pearson correlation table of the entire sample without conditioning. Several structural patterns are readily visible. First, the intra-equity market correlations are high, positive, and statistically significant: S&P 500 and FTSE 100 have a correlation of 0.626, S&P 500 and DAX have a correlation of 0.639, and the highest equity-to-equity correlation is found between FTSE and DAX at 0.852 which reflects the high In comparison, the Shanghai Composite has significantly smaller correlations with all Western equity markets (0.163 with S&P 50, 0.297 with NIFTY 50) reflecting the relatively lower level of financial integration of Chinese equity markets, which is corroborated by capital account management policies and the market structure of the Chinese dominated by domestic investors.

Second, the VIX has a significant negative correlation with all equity indices with the most notable one being -0.738 with S&P 500 which makes it clear that it plays a well-established counter-cyclical role as a measure of global risk aversion. Third, gold has very low, almost zero correlations with the entire equity indices (between 0.058 and 0.090), confirming its portfolio diversifier property. Fourth, and of critical importance to this study, the GPR Index registers near-zero correlations with all variables (ranging from -0.014 to 0.025), suggesting that the unconditional linear relationship between geopolitical risk and financial markets is weak a finding that motivates the dynamic, non-linear TVP-VAR and DCC-GARCH frameworks adopted herein.

Table 5 : Static Pearson Correlation Matrix of Logarithmic Returns (Full Sample)

	SP500	NIFTY	FTSE	DAX	SHANGH.	OIL	GOLD	EXRAT	VIX	GPR
SP500	1.000	0.334	0.626	0.639	0.163	0.342	0.077	-0.202	-0.738	0.004
NIFTY	0.334	1.000	0.473	0.456	0.297	0.210	0.074	-0.299	-0.231	0.009
FTSE	0.626	0.473	1.000	0.852	0.250	0.377	0.084	-0.201	-0.473	0.002
DAX	0.639	0.456	0.852	1.000	0.224	0.306	0.058	-0.215	-0.487	0.003
SHANGH.	0.163	0.297	0.250	0.224	1.000	0.176	0.090	-0.134	-0.130	0.008
OIL	0.342	0.210	0.377	0.306	0.176	1.000	0.185	-0.086	-0.255	0.025
GOLD	0.077	0.074	0.084	0.058	0.090	0.185	1.000	-0.162	-0.042	0.006
EXRAT	-0.202	-0.299	-0.201	-0.215	-0.134	-0.086	-0.162	1.000	0.181	0.021
VIX	-0.738	-0.231	-0.473	-0.487	-0.130	-0.255	-0.042	0.181	1.000	-0.014

GPR	0.00 4	-0.009	0.00 2	- 0.00 3	0.008	0.02 5	0.006	0.021	- 0.01 4	1.00 0
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Note: Values highlighted in red indicate high correlation ($|r| > 0.50$); orange shading indicates moderate correlation ($0.30 \leq |r| \leq 0.50$). Diagonal elements represent unit self-correlations.

4.2 TVP-VAR Connectedness Analysis

4.2.1 Total Connectedness Index - Full-System Dynamics

Figure 3 gives the time-varying Total Connectedness Index (TCI) estimated using the entire ten-variable TVP-VAR system throughout the entire sample period. The TCI is a highly unstable variable, varying between about 28 percent and 65 percent with sharp peaks during significant events in the world. This time dependence is inherent: even a constant VAR would not be able to record these regime-specific amplifications, which highlights the methodological suitability of the TVP-VAR structure.

The sharpest TCI spike is around the collapse of the Lehman Brothers in September 2008 when the interconnectedness peaks at about 65, or 2/3 of the variance of the forecast error of all variables, which is due to the cross-market transmission of shocks in the middle of the GFC. This coincides with the contagion literature (Forbes and Rigobon, 2002; Longstaff, 2010) that records that financial integration increases at an extreme rate during systemic stress. The sharp spike to around 48% is observed later in early 2020, which is the beginning of the COVID-19 pandemic. The demand shock and the extreme risk-off positioning that were synchronised by the pandemic tightened cross-market correlations, and enhanced systemic spillovers among the same group of markets.

The post-2022 period which coincides with the Russia-Ukraine War and the worldwide monetary tightening cycle indicate higher yet weaker TCI values (around 4055 percent), indicating systemic stress which remains persistent but not as severe as the GFC or the COVID-19 pandemics.

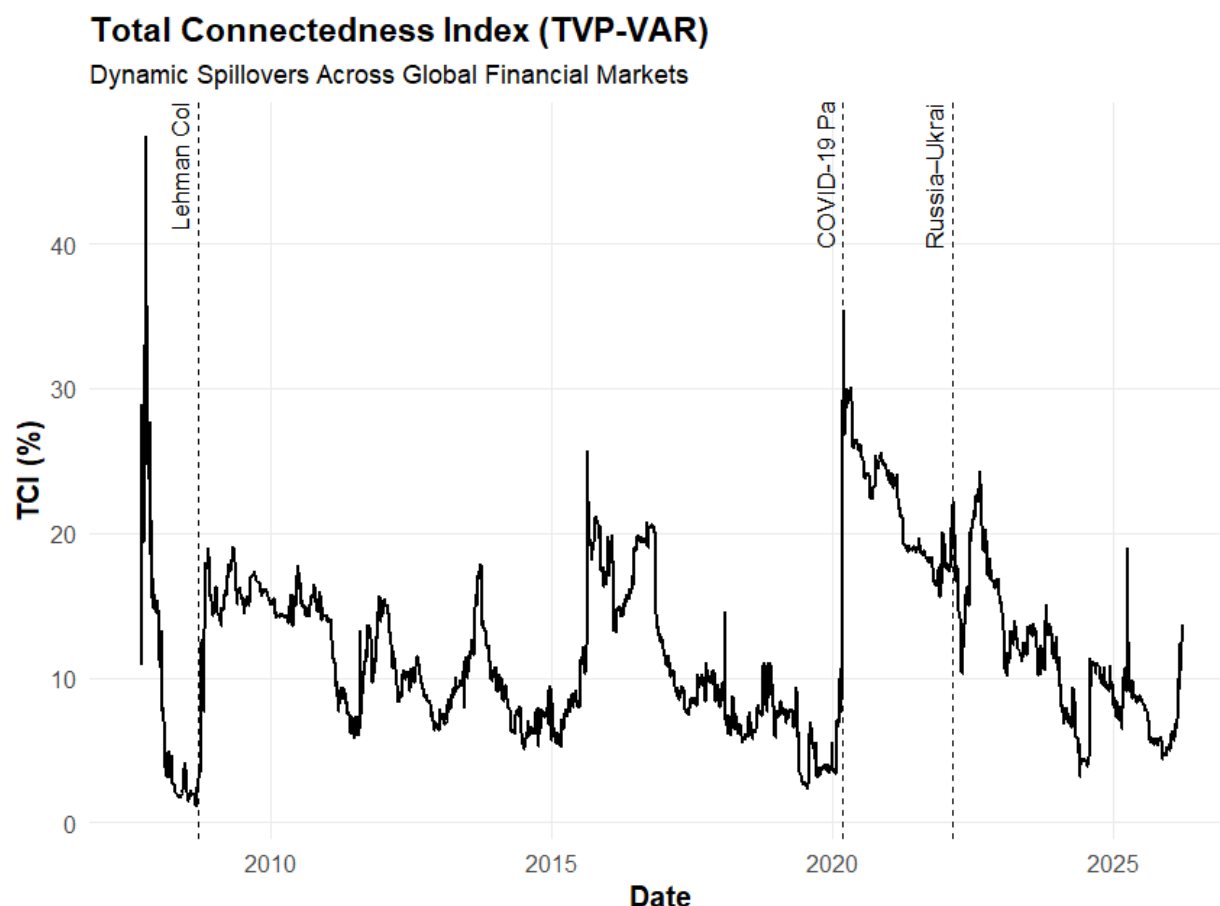


Figure 3 : Total Connectedness Index (TVP-VAR), Full System with Crisis Event (January 2005 – March 2026)

Figure 4 is a complementary visualisation that superimposes the TCI path with colour-coded event bands of the GFC, European Debt Crisis, COVID-19, and the Ukraine War, which further place the crisis-contingent amplification of system-wide connectedness in context. ECD period (2010-2015) shows a moderate yet persistent high level on the TCI with a peak around 2011-2012 when sovereign stress was at its peak in Portugal, Ireland, Greece and Spain. The lowest sustained TCI values (around 35 to 42 percent) are seen during the pre-COVID stability period (2016-2019), which is in line with lower systemic risk, accommodative monetary policies, and a limited geopolitical uncertainty.

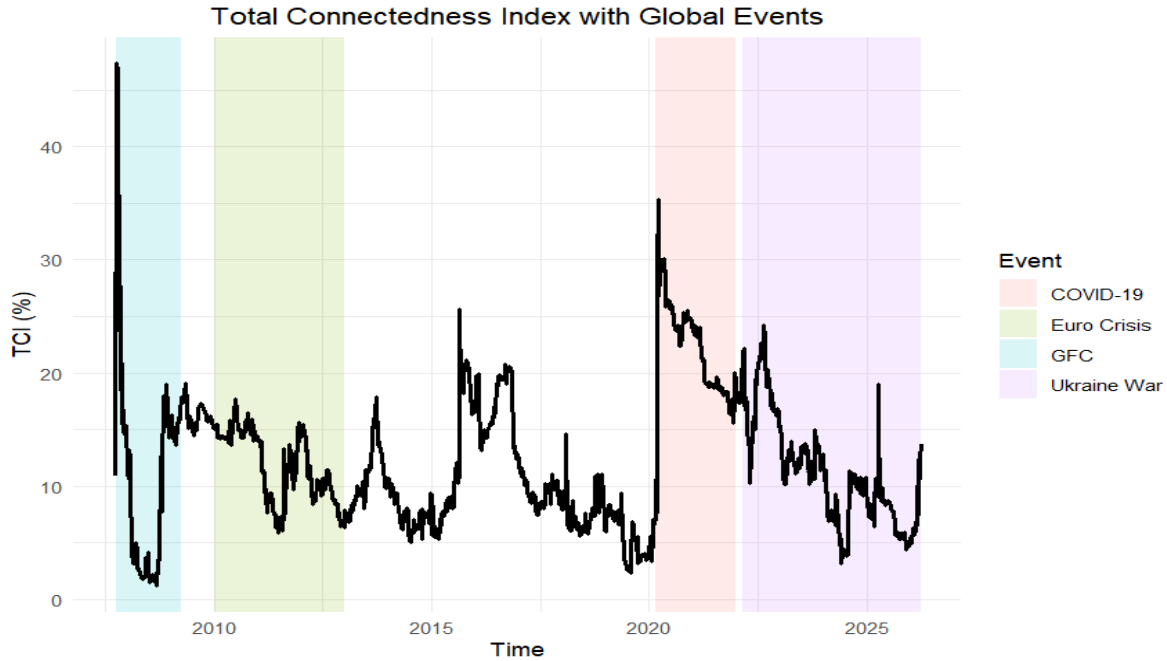


Figure 4 : Total Connectedness Index (SP500–NIFTY–GPR Sub-System) Overlaid with Global Event Bands

4.2.2 Static Directional Spillovers - Full Sample Averages

Table 6 reports average TO, FROM and NET spillovers of the ten variables across the entire sample, obtained as part of the TVP-VAR GFEVD. This directional shock transmission is characterised by these static averages. These findings demonstrate that there is a clear and theoretically consistent hierarchy of spillover transmitters and receivers.

Table 6 : Full-Sample Average TVP-VAR Directional Spillovers (10-Variable System)

Variable	TO (Transmitted)	FROM (Received)	NET (TO – FROM)
S&P 500	76.82	62.42	+14.40
NIFTY 50	36.90	44.95	–8.05
FTSE 100	77.16	63.61	+13.55
DAX 30	76.67	63.36	+13.31
Shanghai Composite	17.43	28.44	–11.01
Brent Crude Oil	30.45	34.73	–4.28
Gold	13.18	21.16	–7.98
USD Index (DXY)	17.75	33.56	–15.80
VIX	65.48	58.13	+7.36
GPR Index	5.49	6.99	–1.50

Note: NET = TO – FROM. Positive NET values (green) denote net transmitters; negative values (red) denote net receivers. All figures are expressed as percentages of forecast error variance.

The S&P 500 (NET = +14.40%), FTSE 100 (+13.55%), and DAX (+13.31%) become the leading net transmitters of shocks into the system and confirm the primacy of the developed Western equity markets in global financial contagion. This result supports Hypothesis H3 and it is also in agreement with the literature on cross-market contagion (Bekaert *et al.*, 2005). The VIX is uniquely placed as a net transmitter (+7.36%) in the sense that it is not just a measure of sentiment, but a proactive propagator of volatility expectations in the global markets, especially in the cross-asset repricing channels as (Whaley, 2000) and (Sarwar, 2012).

In contrast, the Shanghai Composite (−11.01%), the USD Index (−15.80%), NIFTY 50 (−8.05%), and Gold (−7.98%) are unambiguous net receivers of shocks. The net receiver character of the USD Index is especially interesting: this suggests that the stress in the global equity markets and commodity shocks are more likely to impact the dynamics of the exchange rates than the other way and it can be the result of the reserve currency position of the USD and the flight-to-quality process in times of crisis. It does not follow that safe-haven status of gold is violated by its net receiver position (as it receives more than it sends) but, in fact, this may imply that in crises, the price of gold is sensitive to equity market shocks, but it also offers a diversification hedge, as (Baur and Lucey, 2010). The GPR Index records the lowest TO and FROM spillovers (5.49% and 6.99%, respectively), meaning that although geopolitical risk propagates any given spillovers to financial markets, financial market dynamics do not significantly contribute to the GPR measure an interpretively significant asymmetry.

4.2.3 Net Spillover Dynamics — Time-Varying Evolution

Figure 5 follows the time-varying net spillover paths of all ten variables in the entire sample. The number validates that there is a significant difference in time in directional roles: some of the variables fluctuate between net transmitter and net receiver designation in various regimes, and some of them have consistent directional roles. It is notable that the increase in net spillovers in the GFC period is highest in the case of Western equity markets (S&P 500, FTSE, DAX) and VIX which explode into net transmitter territory. On the other hand, Shanghai Composite, NIFTY 50 and gold are always in net receiver regions during crisis episodes and this supports the structural hierarchy in **Table 5**. Another major reversal occurs during the post-2022 period: the GPR Index displays short-lived but steep excursions into the net transmitter territory, as it is expected by the hypothesis that geopolitical risk is a direct propagator of financial market shocks when geopolitical uncertainty is high and persistent (Caldara and Iacoviello, 2022).

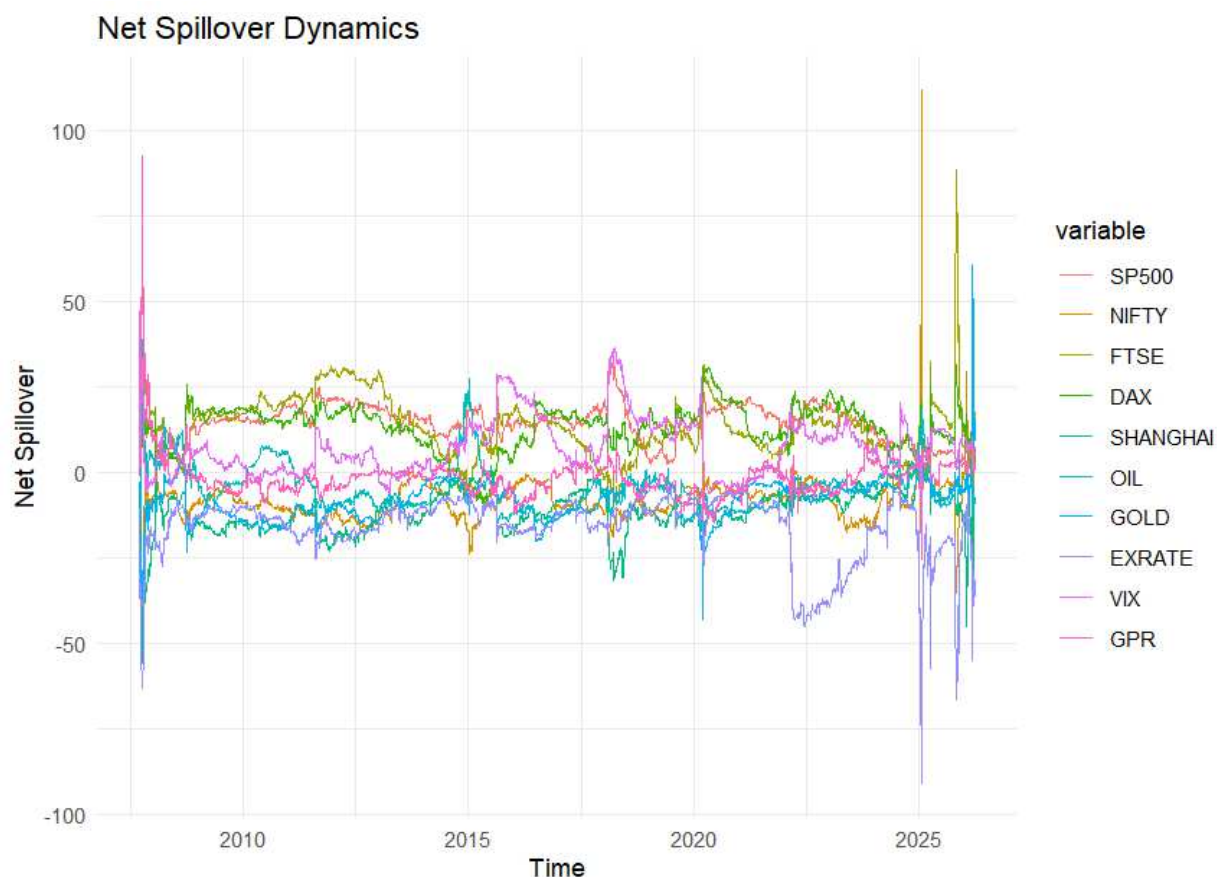


Figure 5 : Net Spillover Dynamics — All Variables (TVP-VAR, Full System)

4.2.4 Focused Sub-System: SP500–NIFTY–GPR Connectedness

In **Figure 6** and **Figure 7**, the TCI and net spillover dynamics of the targeted three-variable sub-system of the S&P 500, NIFTY 50, and GPR Index are shown. The theoretical interest of this sub-system is it directly tests Hypotheses H1 and H2 on whether geopolitical risk is one of the drivers of equity market spillovers. The TCI sub-system (**Figure 6**) shows acute spikes at the beginning of the GFC (around 47) and the COVID-19 shock (around 36), with intermediate increases at the time of EDC and after 2022. Most importantly, the absolute level of the sub-system TCI is significantly lower than the full-system TCI (topping at around 47% vs. 65%), indicating that much of the connectedness of the entire system takes place within the European equity markets (FTSE, DAX) and within the VIX channel, not considered in the sub-system.

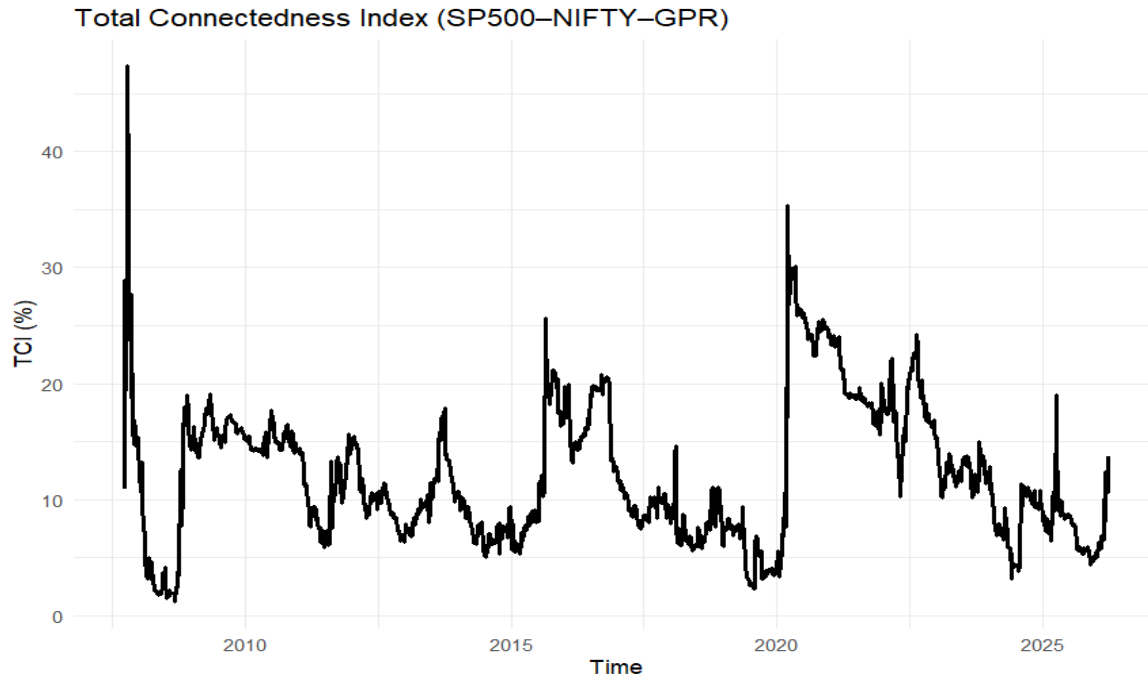


Figure 6 : Total Connectedness Index — SP500, NIFTY 50, and GPR Sub-System

Figure 7 affirms that in this sub-system, S&P 500 is the net transmitter, by far, during the GFC (surging to about +70 net spillover units in early 2008), and NIFTY 50 is the net receiver. GPR shows that most of the sample has near-zero net spillovers but records short episodes of positive net transmitter during the 2019/2020 US China trade tensions and the 2022 Russia - Ukraine War, which is in line with the episodic hypothesis of geopolitical risk transmission (Hypothesis H1).

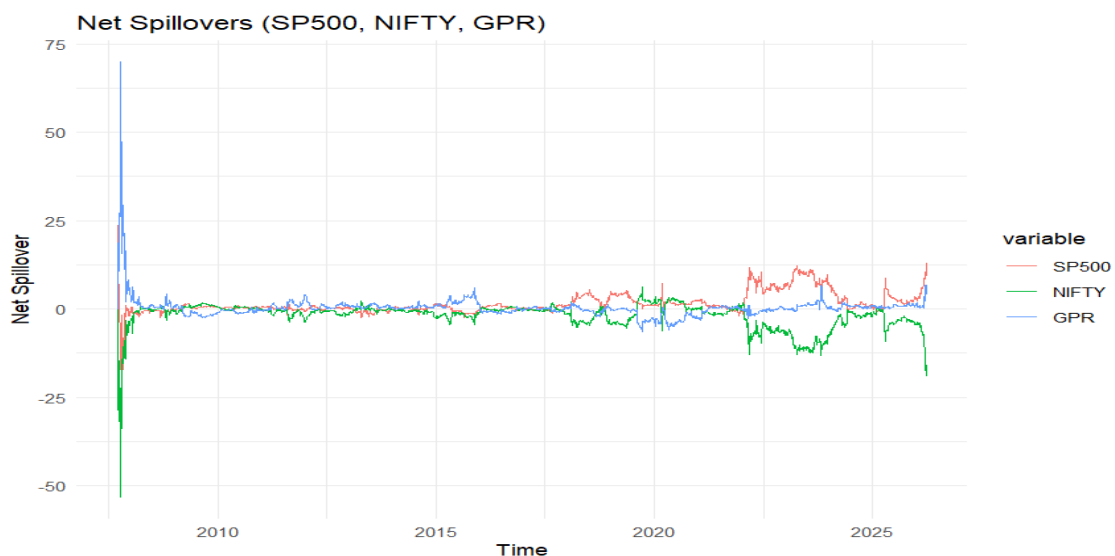


Figure 7 : Net Spillovers — SP500, NIFTY 50, and GPR Index Sub-System

4.2.5 Sub-Period TVP-VAR Connectedness Summary

Table 7 summarises the average TCI and net spillover positions of the S&P 500, NIFTY 50, and GPR Index across the five sub-periods. The results reveal important regime-dependent patterns in systemic connectedness.

Table 7 : Sub-Period Average TVP-VAR Connectedness — SP500, NIFTY, and GPR

Sub-Period	Avg. TCI (%)	Net SP500	Net NIFTY	Net GPR
GFC (2005–2009)	16.63	+6.00	−6.42	+0.42
EDC (2010–2015)	10.55	+0.10	−1.14	+1.05
Pre-COVID (2016–2019)	7.51	−1.22	−1.50	+2.72
COVID (2020–2021)	25.58	−0.01	−1.51	+1.52
War Period (2022–2026)	8.76	−1.47	−2.02	+3.49

Note: TCI is expressed as the average percentage of forecast error variance explained by cross-variable spillovers within the SP500–NIFTY–GPR sub-system. Net values represent average net directional spillovers in percentage units.

The COVID-19 period registers the highest average TCI (25.58%), followed by the GFC (16.63%), the War period (8.76%), the EDC (10.55%), and the pre-COVID baseline (7.51%). The COVID-19 prevalence in sub-system TCI is the manifestation of the globally synchronised nature of the pandemic shock that simultaneously impacted all asset classes and caused the highest level of uncertainty to ever be experienced across markets. The GPR Net spillover pattern particularly deserves attention: GPR goes through the modest net transmitter (−0.42) during the GFC to the significantly larger net transmitter position during the War period (−3.49), which indicates a structural change of the financial market relevance of the geopolitical risk in the post-2022 setting and directly proves Hypothesis H1.

4.3 Dynamic Conditional Correlation Analysis

4.3.1 Time-Varying Bilateral Correlations

Figure 8, Figure 9, Figure 10 present the DCC-GARCH-estimated time-varying correlations for three key pairs: S&P 500–NIFTY 50, S&P 500–GPR, and NIFTY 50–GPR, respectively. These bilateral paths provide granular insight into the evolution of market co-movement that the aggregate TCI masks.



Figure 8 : DCC-GARCH Time-Varying Correlation S&P 500 vs NIFTY 50

Figure 8 S&P 500 NIFTY 50 correlation range the correlation range between S&P 500 and NIFTY 50 is in the range of 0.25 to 0.40 with the average of the entire period being 0.2917. Such a positive and moderate co-movement indicates the gradual financial integration of the Indian equity markets with the world capital markets during the twenty years. Most notably, the correlation peaks (around 0.39-0.40) in the 2014-2015 period (related to the inclusion of the Indian market in global indices and the large influx of foreign institutional investors) and once again in the period of the first COVID-19 shock (2020) when the diversification benefit of the Indian geographic market separation was briefly reduced as every country rebalanced its This post-2022 phase indicates a slow normalisation of 0.27-0.30, which is consistent with the fact that India has a relatively stronger domestic economic resilience and idiosyncratic growth drivers than the US amid the inflationary tightening cycle.

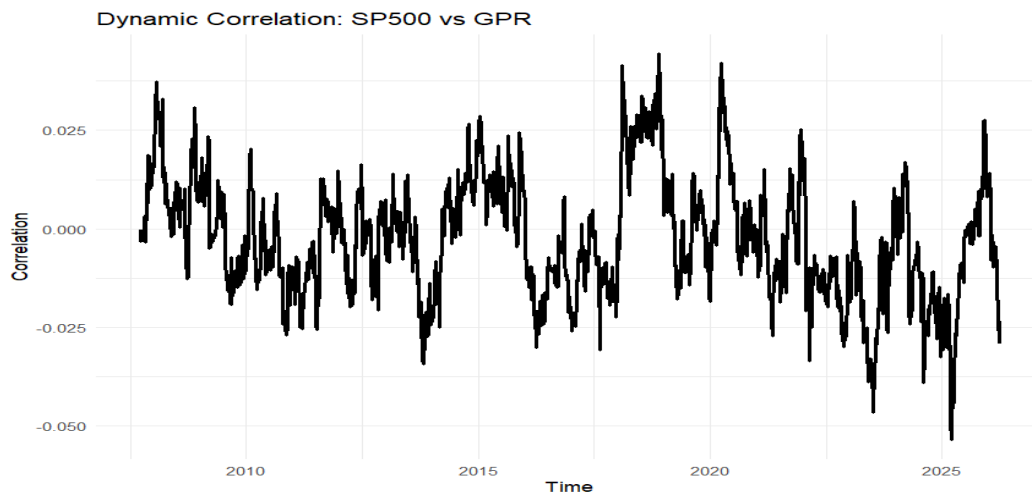


Figure 9 : DCC-GARCH Time-Varying Correlation S&P 500 vs GPR Index

Figure 9 S&P 500- GPR correlation has a very small range of values, and the average correlation of the full sample is -0.0026. The almost zero unconditional correlation validates the previous results of the statical correlation table **Table 5**.. Nevertheless, the time-varying path indicates significant episodic deviations: the correlation becomes slightly positive in the 2019-2020 period (around +0.03), when the US-Iran tensions intensified, the US-China trade war intensified, and the COVID-19 causes geopolitical uncertainty. On the other hand, the correlation becomes sharply negative beyond 2022 (around -0.050), which shows that during the Russia-Ukraine War period, the high geopolitical risk is primed with the negative equity returns a flight-from-risk pattern that is in line with Hypothesis H1. Such regime-dependent asymmetric relationship between equity markets and geopolitical risk highlights the relevance of dynamic modelling; a static correlation coefficient of -0.003 would simply mask this crisis-related co-movement pattern.

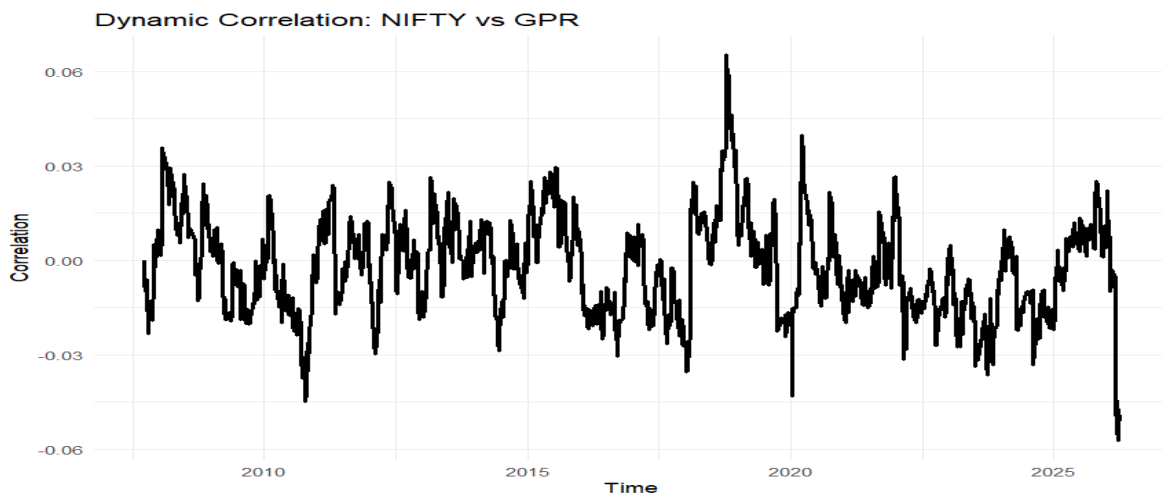
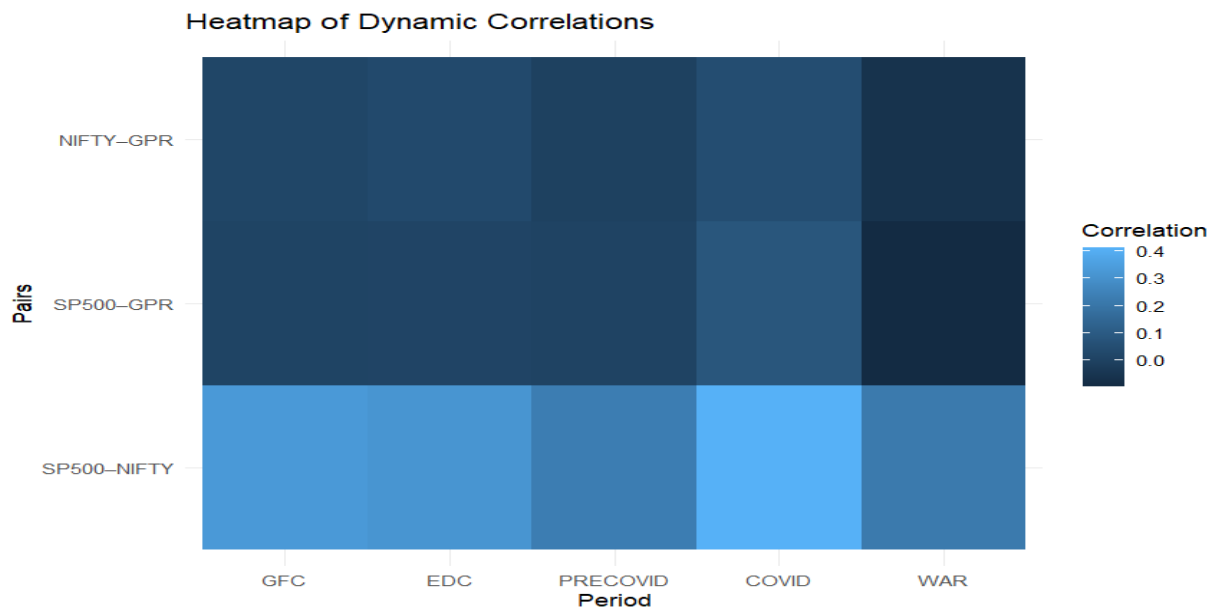


Figure 10 : DCC-GARCH Time-Varying Correlation — NIFTY 50 vs GPR Index

The NIFTY 50-GPR correlation (**Figure 10**) has a rather similar pattern compared to the S&P 500-GPR pair, with the oscillation around zero with some occasional deviations. The largest positive spike is in the early 2020 (+0.065) which is probably due to the domestic geopolitical sensitivity of India at the time of the COVID-19 lockdown coupled with the border tensions with China. The period after 2022 War is found to have a stronger negative relationship (around -0.055), replicating the S&P 500-GPR activity, but with a somewhat larger value perhaps due to a greater exposure of India to geopolitical risks as regional power as close to the areas of active conflict and a large importer of both crude oil (disrupted geopolitically) and defence equipment. The average

of the full period (-0.0022) is almost equal to zero, yet again justifying the dynamic modelling



approach.

4.3.2 Sub-Period DCC Correlation Analysis

The average dynamic correlations in the five sub-periods are shown as bar chart and heatmap in **Figure 11** and **Figure 12** respectively. A combined panel of the TCI time series and the sub-period DCC correlation nexus is presented in **Figure 13** which gives a holistic view of the connectedness correlation nexus. **Table 8** the sub-period average DCC correlations of three most important pairs.

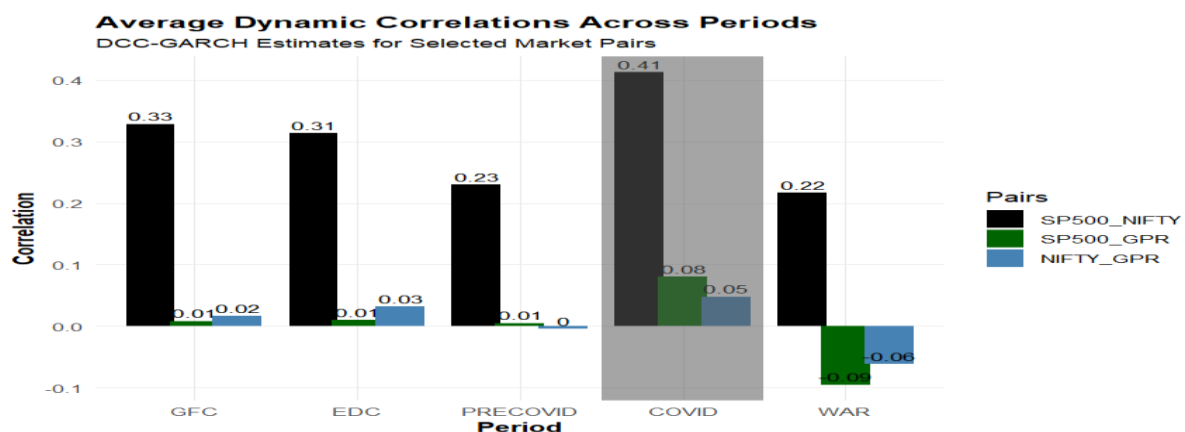


Figure 11 : Average Dynamic Correlations Across Sub-Periods — DCC-GARCH Estimates (SP500–NIFTY, SP500–GPR, NIFTY–GPR)

Figure 12 : Heatmap of Average DCC Correlations by Market Pair and Sub-Period

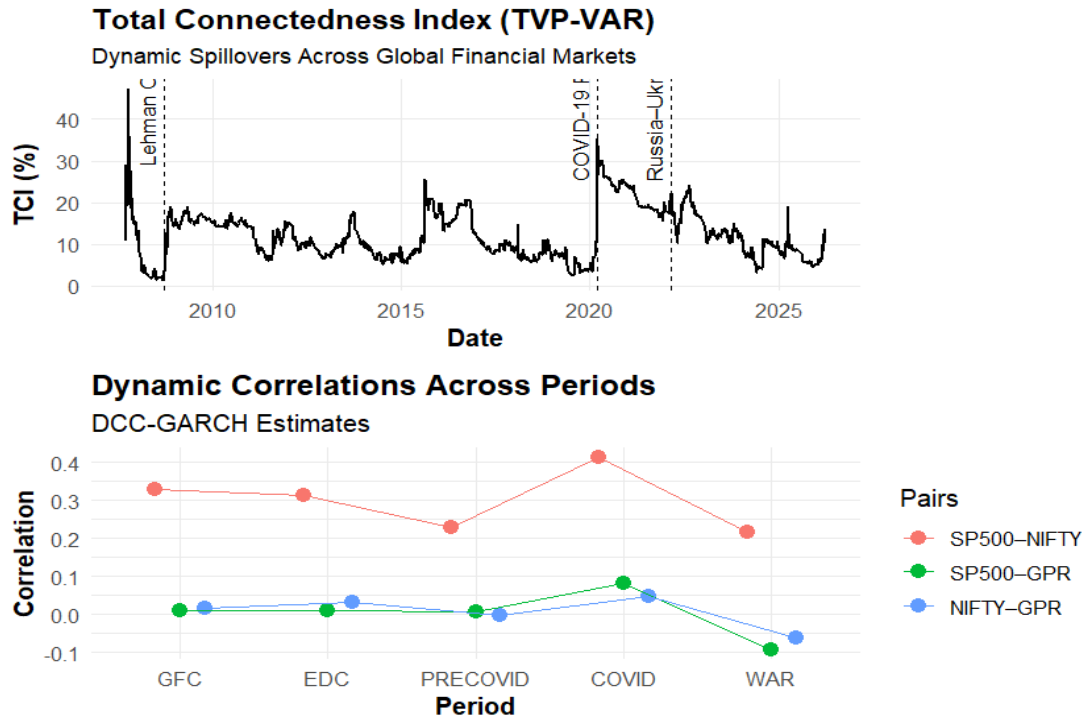


Figure 13 : Combined Panel — TCI (TVP-VAR) and Dynamic Correlations Across Sub-Periods (DCC-GARCH)

Table 8 : Sub-Period Average DCC-GARCH Correlations for Selected Market Pairs

Sub-Period	SP500–NIFTY	SP500–GPR	NIFTY–GPR	TCI (%)
GFC (2005–2009)	0.3287	+0.0085	+0.0165	16.63
EDC (2010–2015)	0.3139	+0.0098	+0.0320	10.55
Pre-COVID (2016–2019)	0.2300	+0.0053	–0.0041	7.51
COVID (2020–2021)	0.4124	+0.0804	+0.0481	25.58
War (2022–2026)	0.2174	–0.0948	–0.0616	8.76

Note: Positive SP500–GPR and NIFTY–GPR values indicate geopolitical risk positively co-moves with equity returns within the period; negative values indicate an inverse relationship. Full-sample average SP500–NIFTY correlation = 0.2917.

The DCC results of the sub-period show some theoretically significant patterns. The correlation between S&P 500 and NIFTY 50 is highest during the COVID-19 period (0.4124) and lowest during the War period (0.2174), which is plausibly due to the structural decoupling of the equity market in India to the US markets in the post-2022 environment and the fact that India is a geopolitical beneficiary of diversification

The period of GFC and EDC both report higher SP500-NIFTY correlations (0.33 and 0.31, respectively) which concurs with the observation that systemic financial crises produce contagion that supersedes the benefits of diversification (idiosyncratic). More importantly, both the SP500 and NIFTY correlations with GPR show an inversion of the sign between the COVID-19 and War periods. Both pairs report their largest positive values during the COVID-19 period (+0.080 and +0.048, respectively), indicating that the pandemic-related GPR positively co-moved with the equity markets - perhaps due to high levels of uncertainty about the pandemic causing a higher index of geopolitical risk coupled with simultaneous massive fiscal and monetary stimulus that validated equity values. In comparison, in the period of the War (2022-2026) both correlations become negative (SP500GPR: -0.095; NIFTYGPR: -0.062), which is a sign that in a typical geopolitical shock, which is characterised by a supply shock and inflation pressure without corresponding monetary stimulus, high geopolitical risk is converted into equity market decline. This sign reversal is a new and significant observation, which has not been fully captured in the literature, which mostly employs a static or short-sample methodology.

4.4 Connectedness, Correlations, and Geopolitical Risk Across Regimes

Taken together, the TVP-VAR and DCC-GARCH results provide a multi-dimensional picture of global financial market interdependence that evolves non-linearly with the nature and severity of the underlying shock. **Figure 14** consolidates the full-system net spillover dynamics to facilitate the identification of crisis-period role reversals and persistent structural hierarchies.

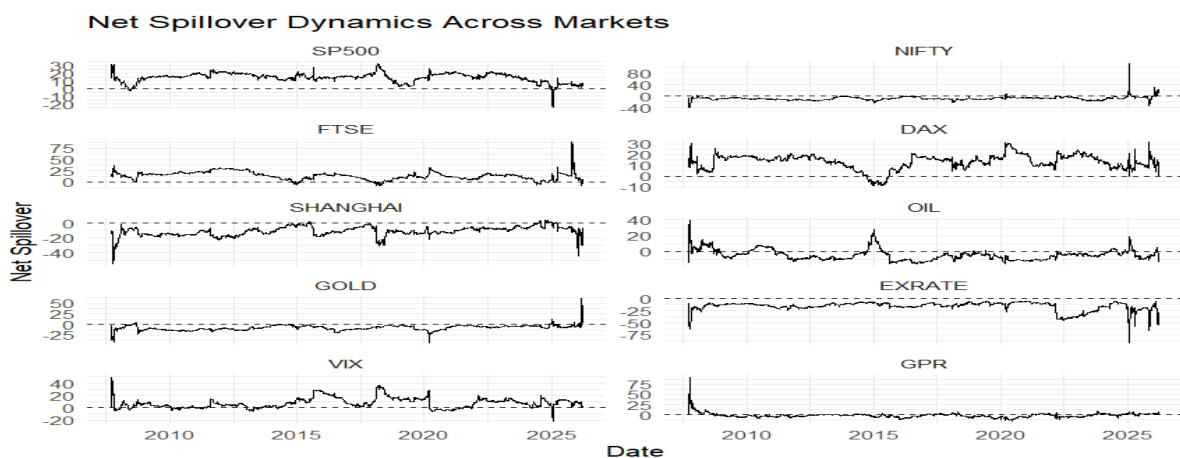


Figure 14 : Net Spillover Dynamics — SP500, NIFTY, and GPR (Extended Full-Sample View)

This synthesis yields three broad findings. To begin with, systemic connectedness is clearly crisis contingent. The two apex events of interconnectedness in the financial market in the 21-year sample were the GFC and the COVID-19 with the TCI values higher than 16% and 25% in the sub-system and the entire system, respectively. This result directly confirms the Hypothesis H2 that connectedness between global financial markets is time-varying and magnifies during crisis times - and offers solid empirical evidence to the dynamic modelling strategy used herein.

Second, most variables are structurally persistent in terms of identity of net transmitters and receivers, but GPR is geopolitically contingent in this regard. The S&P 500, FTSE and DAX are always the largest net transmitters, affirming the systemic centrality of developed Western equity markets, in line with Hypothesis H3. The GPR Index, though, shows a monotonically rising net transmitter position between sub-periods - +0.42 (GFC) to +3.49 (War period) meaning that the financial relevance of geopolitical risk has been on the rise over time, especially in the post-2022 context of structurally high and enduring geopolitical tensions.

Third, the reversed signs of equity-GPR dynamic correlations during the COVID-19 and War periods indicate that there is an essential difference between pandemic-type and geopolitical-conflict-type uncertainty: the former is accompanied by an increase in equity market prices under the influence of policy stimulus and the latter creates stagflationary pressures that at the same time reduce the prices of the equity market and increase the level of geopolitical risk. This subtle observation has significant implications in the construction of a portfolio, the use of hedges, and the policymakers who observe systemic risk, and it is the motivation behind the formal hypotheses evaluated in the discussion section that follows.

5. Discussion

The empirical results emphasize several significant features of the world financial markets and how they relate to the geopolitical risk. Descriptive statistics show that the excess kurtosis and the negative skewness rates are present in majority of financial series, which are characterised by extreme events and asymmetric risk. The correlation analysis indicates that developed equity markets have high levels of integration and especially between the US and European indices, whereas emerging market economies like China have weaker integration levels.

Gold has low correlation with equities, which is justifiable, as it is used in diversification, but the volatility index (VIX) has high negative correlations with stock markets, which justifies its use as a fear gauge (Whaley Robert, 2000). By contrast, geopolitical risk demonstrates almost zero contemporaneous correlations with most financial variables, indicating that its impact is indirect and might manifest itself mostly in times of increased uncertainty. The TVP-VAR outputs give more information on the market structure of transmission of shocks. The developed markets, particularly the US and major European indices are found to be the net transmitters of shocks, which validates their central position in the world financial system. On the other hand, the emerging markets, commodities and exchange rates are mostly net receivers, which means that they are vulnerable to external forces. The volatility index is also a significant transmitter, and uncertainty is important in intensifying the effects of spillovers (Gheorghe and Panazan, 2025). Geopolitical risk is part of the system but is relatively less significant to overall connectedness and is typically a net receiver, implying a minor, yet non-trivial, part in the transmission process.

The dynamic analysis indicates that financial connectedness and correlations are very time-varying and responsive to international events. The overall connectedness index is much higher in a major crisis like the global financial crisis and the COVID-19 pandemic, which implies that the market is better integrated in times of crisis. Equally, the crises also lead to a rise in correlation between equity market, diminishing the benefits of diversification (Aslam and Newaz, 2025). Although geopolitical risk presents weak average effects, the impact of this risk is stronger in times of stress, and the correlation patterns change to reflect the change in investor behaviour and perception of risk.

6.Implications

6.1. Managerial Implications

The results are relevant to investors, portfolio managers and financial institutions. The empirical results are consistent with high time-varying connectedness, implying strong financial contagion that varies significantly across different regimes. Thus, portfolio managers should not solely assume that the historical average correlation will hold true when determining risk exposure. Conventional diversification strategies lose their effectiveness during crises when there are increased correlations across global equity markets. This is a reminder to the importance of flexible asset allocation strategies which can adapt to market conditions. Further, the results show that the average correlation of geopolitical risk with financial markets should not be regarded as negligible and therefore be ignored. It is more evident when the world is under stress, implying that investors should consider geopolitical risk for tail-risk hedging, stress testing, and scenario-based portfolio strategies. The VIX's role as a net transmitter also highlights the importance of markets' uncertainty channels and their sentiment. Integrating forward-looking volatility indicators into financial institutions' risk management systems can therefore be of benefit.

6.2. Theoretical Implications

This paper is a unique addition to the literature on financial connectedness, contagion and geopolitical risk as it demonstrates that spillover effects and correlation structure are not fixed but rather variable. The results corroborate the notion of regime-dependent interdependence between global financial markets, defined here as the extent to which spillovers are strong and direction of spillovers varies between the normal and crisis stages. Net exporting areas of the global financial system are dominated by developed economies like the U.S. and European markets, which confirms a core-periphery structure in the global financial system. This offers a theoretical basis for the argument that the impact of shocks can be disproportionately distributed to emerging and peripheral markets from major financial centres.

6.3. Policy Implications

The ability of regulatory frameworks to capture the contagion of shocks, especially during crisis periods like the Global Financial Crisis and the COVID-19 pandemic, is highly regime-specific and may not be enough to ensure a stable outcome.

The regulators thus need to take a countercyclical approach to macroprudential policy that is more proactive when systemic risks are high. The results show that developed markets are key net transmitters which makes emerging economies more susceptible to shocks from key financial centers. Financial resilience in emerging markets should be increased by diversifying capital flows, maintaining adequate foreign exchange reserves and strengthening financial systems. These measures can help to mitigate the negative impacts of external financial shocks. In the case of VIX, being a net transmitter shows the significance of adding forward-looking uncertainty measures to financial stability monitoring frameworks. The traditional measures of macroeconomic indicators will not necessarily be enough to catch signs of systemic risk early. Hence, indicators based on markets should be also part of the early warning systems, including volatility indices, global risk sentiment indicators and geopolitical risk indicators.

7. Conclusion

This paper gives a detailed discussion of the dynamic spillover effects and time-varying correlation structure of world financial markets and geopolitical risk during the years 2005-2026. The analysis by using a massive methodological framework that incorporates TVP-VAR and DCC-GARCH models, not only captures systemic interconnectedness but also captures the changing bilateral relationships in various economic regimes.

The results validate that financial markets around the world are highly interdependent with developed equity markets serving as key agents of transmitting shocks. These spillovers are generally very sensitive to the state of crisis, and systemic connectedness is greatest when disruptions to the global system are of enormous scale, e.g. the Global Financial Crisis and the COVID-19 pandemic. Such periods are typified by increased market synchronization and less diversification opportunities. Geopolitical risk is not a compelling force in the normal state of affairs but it becomes a significant force during times of high uncertainty. Its effect is not only time-varying, but asymmetric, which has a different effect on markets depending on the macro-financial environment. This shows that geopolitical factors should be included in financial risk assessment systems. In general, the paper highlights how financial interconnectedness is dynamic and not static and how spillovers and correlations change in reaction to global shocks. The insights add to the deeper insight into systemic risk and give valuable guidance in the design of adaptive risk management.

Lastly, the study recommends using multi-layered analytical frameworks incorporating both spillover and correlation dynamics to be used by policy makers and financial institutions. These all-in-one models can give more precise information which can inform decision-making in times of economic turmoil and can enhance the design of timely and effective policy responses.

8. Limitations and Future Research

Granted, this study does present some valuable insights, but it is limited by some limitations which also provide the opportunities to research in the future. The analysis is mostly model-dependent and based on the TVP-VAR and DCC-GARCH models, which, though well-performing, might not be comprehensive to nonlinear dependencies, tail-risks, and sudden structural changes in extreme market scenarios. Also, the variables used, which are restricted to major equity indices, commodities, exchange rates and one geopolitical risk index, might not fully reflect the entire range of global financial interconnections. The major spillovers like bond markets, cryptocurrencies, and derivatives are omitted, which might not capture other avenues of transmitting the spillovers.

Moreover, the geopolitical risk index employed might not capture the heterogeneity of a region or the current geopolitical trends completely thus influencing the accuracy of the findings. Daily data, though suitable in terms of capturing medium-term dynamics, also restricts the possibilities of observing high-frequency spillovers and intraday market responses. Lastly, despite the directional spillovers found in the connectedness framework, the framework does not prove actual economic causality, meaning that the results should be interpreted with caution. The analysis of extreme events and dynamic dependencies could be improved by using high-frequency data and sophisticated methods of econometric or machine learning like regime-switching models, copula-based methods, or nonlinear frameworks. Also, more detailed regional or sectoral analyses might be able to show non-homogeneous spillover patterns masked in aggregated models.

Further extending the framework to policy-based applications, including stress testing in hypothetical geopolitical situations, would render it even more practical. The introduction of new dimensions such as climate and ESG-related risks can also offer a more comprehensive view of the dynamic nature of the global financial market interconnectedness.

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