

Exploring Time–frequency Quantile Connectedness Among Major Automobile Sectors and the Global Energy Market: Evidence from India, China, the United States and Japan

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Abstract

Understanding the transmission of shocks across global automobile markets and energy markets has become increasingly important in an era of economic uncertainty, geopolitical tensions and evolving mobility transitions. The study examined the time-frequency quantile connectedness of 4 major automobile markets, namely the USA, China, India and Japan, with the global oil market for a time period of 10 years, from 2016 to 2026. The study employs the Quantile Vector Autoregression (QVAR) approach for inspecting the time and frequency domains of connectedness. The study reveals that connectedness is substantially high during extreme positive and extreme negative market conditions. Furthermore, the USA automobile market is the key transmitter of shocks to the rest of the market across all quantiles, whereas the Oil market is the key recipient during extreme conditions. In the frequency domain, the Total Connectedness Index (TCI) is asymmetric for the short run and long run. The directional analysis further shows that the role of a market is not fixed. Every market alternate between transmitter and receiver based on the prevailing quantile and time horizon. The key takeaway is that mean-based connectedness measures understate cross-market risk during extreme market positive and negative moments, reinforcing the need for quantile-based measures. These findings carry direct implications for quantile-specific hedging strategies, cross-border portfolio diversification and risk monitoring during global uncertainties.

Keywords: Automobile Stock Markets, Crude Oil Price, Quantile Vector Autoregression (QVAR), Tail Risk, Time-frequency Connectedness.

Introduction

Global automobile markets have become increasingly interconnected due to globalisation, supply-chain integration and international capital mobility. Any disruption in any part of this chain will have a huge impact on the global automobile sector. According to the World Population Review 2026 data, China, the USA, Japan and India are the leading automotive manufacturing hubs. These four nations hold the major automotive production in developed and emerging countries. Furthermore, the selection is based on total vehicle production volume, rather than passenger car outputs. Countries like Germany and South Korea have a better position in passenger car production than the USA, whereas the USA stand second in the overall market, with the support of the highest production in commercial vehicles. The combined production of the European market and the rest of the market remains smaller than the top four markets and identifies the extension to the

European market as an avenue for future research. Given their heavy reliance on fuel-intensive manufacturing and logistics, these sectors maintain a complex, time-varying sensitivity to crude oil price fluctuations (1). This sensitivity is particularly pronounced during extreme market conditions, where volatility spillovers across these major economies exhibit significant asymmetry compared to normal trading periods (2). Also, the integration of these sectoral markets with global energy prices often experiences heightened contagion at extreme quantiles, necessitating a robust examination of tail-risk transmission across distinct frequency domains (3, 4). As one of the primary energy sources, oil creates a ripple effect across the industry (5, 6). From production cost to consumer demands, the automobile sector claims the third largest consumer of oil. This deep-rooted dependence on oil serves as a primary catalyst for the essential transition currently reshaping the

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sector (7). The transition towards electric vehicle production in these nations is reshaping connectedness dynamics, as the shift from internal combustion engines to battery electric vehicles decouples automobile stocks from oil volatility, requiring an analysis of this structural divergence (7).

The automobile industry has also become vulnerable to extreme global events like the Global Financial Crisis, the COVID-19 pandemic, the Russia-Ukraine conflict, semiconductor shortages, and the Iran-US war. These have amplified cross-market dependencies, often triggering a shift from long-term to short-term transmission mechanisms (8). During extreme market conditions, diversification opportunities narrow significantly as financial and commodity markets move together, and volatility spillovers between crude oil and these regional automotive indices exhibit marked time-varying patterns, with nations transitioning between net transmitters and recipients depending on prevailing macroeconomic volatility (9). Existing empirical studies, however, frequently neglect this nuanced interaction at different quantile levels, and standard mean-conditional approaches obscure how spillover intensity fluctuates during turbulent market phases (10). Understanding these dynamics has therefore become highly relevant for investors, policymakers and financial market participants.

Studies have explored the connectedness, quantile connectedness and spillover effects across different stock markets, foreign exchange markets and commodity markets using different Vector Autoregression (VAR)-based connectedness frameworks (11-13). The most widely used methodology in financial connectedness research is the spillover approach, pioneered by (14-16). This connectedness study was further extended to the frequency domain by decomposing spillover into short- and long-term (17). Recently, the introduction of the quantile connectedness framework has helped to capture tail-dependent and asymmetric spillovers under extreme market conditions (18).

Several researchers have explained the relationship between automobile stock and the oil market (1, 19-27). To our knowledge, the existing studies have never explored the quantile connectedness methodology in the major automobile market players and the oil price.

By integrating the quantile connectedness methodology with frequency-domain decomposition, this research provides a comprehensive assessment of how cross-market spillovers evolve across varying temporal horizons and tail risk conditions (20, 28). This approach is particularly valuable for identifying idiosyncratic risk shocks that manifest during periods of heightened market turbulence, where traditional mean-based models fail to capture the nuances of extreme event propagation (29).

The growing interdependence of global automobile markets as well as the electric transition underway in the automobile sector underscores the need to examine how the four largest automotive economies respond to extreme events within a time-frequency framework. The time dimension captures how spillover patterns evolve, while the frequency dimension isolates the persistence of these shocks, distinguishing transitory noise from long-term structural dependencies (30). The study not only addresses a clear gap in the sector-level connectedness literature but also offers a methodological template that can be extended to other energy-intensive sectors, emerging market configurations, and alternative commodity-equity systems.

Based on the discussion above, this study addresses the following research questions:

- (a) How does the connectedness between the top four automobile markets and the oil price behave during extreme market conditions?
- (b) Which automobile markets act as net transmitters or net receivers of shocks across different market conditions?
- (c) How does the connectedness structure differ between short-run and long-run frequency components?

The study makes the following primary contribution by addressing these questions: To our knowledge, this is the first study to apply a quantile connectedness framework to the top four automobile sectors. The study integrates time-frequency decomposition to distinguish short-run from long-run transmission channels at each quantile. The ten-year data period covers the major shock episodes, which helps to evaluate how connectedness evolves during extreme situations and normal days.

Methodology

Figure 1 summarises the overall experimental flow chart from data collection to the interpretation of connectedness measures across quantiles and frequency domains. The major focus of the study is to examine the tail connectedness between crude oil price and four major automobile Sectors. Key automobile market players such as China, India, the United States and Japan are taken into account for a period of 10 years, from April 2016 to March 2026. Major crises during these periods are: the

post-2015-2016 global oil crash, the USA-China trade war, the COVID-19 pandemic and the global semiconductor shortage that curtailed automobile production worldwide (31). Also, the Russia - Ukraine war and the initial impact of the Strait of Hormuz blockade. Moreover, the transition towards clean energy in the automobile sector also reshaped the relationship between the automobile and oil markets.

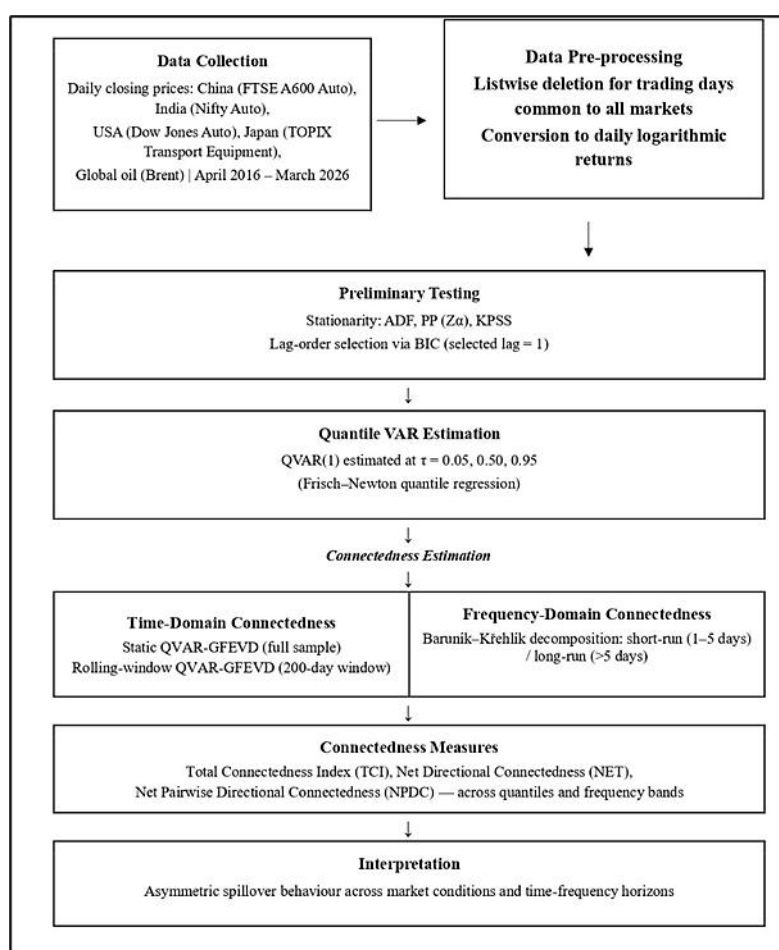


Figure 1: Experimental Flow Chart

The five major indices employed in the study are as follows: we use the FTSE A600 Automobile and Parts Index, which tracks the equity performance of automobile and auto-components manufacturers listed on the Chinese A-share market and serves as the most comprehensive sectoral benchmark for China's domestic automotive industry. For the Indian automobile sector, the Nifty Auto Index, comprising the largest and most liquid automobile stocks listed on the National Stock Exchange of India, covering passenger vehicles, commercial vehicles, two-wheelers and

auto-ancillary companies, has been taken. Dow Jones Automobile Index, which captures the performance of major U.S.-listed automobile manufacturers and parts suppliers, is taken for this study. TOPIX Transportation Equipment Index, listed on the Tokyo Stock Exchange, covers the Japanese market. Finally, crude oil is represented by the Brent Crude Oil spot price. The internationally dominant benchmark for global oil pricing and the most relevant reference price for oil-importing economies (32). All the automobile-related information is sourced from investing.com.,

Brent oil data is extracted from the EIA website (33).

Daily frequency data are utilised for all five variables. Observations corresponding to days on which any one of the five markets was closed due to national holidays or any other factors are handled through listwise deletion, retaining only trading days common to all markets. This synchronisation process ensures the internal consistency of the time series, mitigating potential biases arising from asynchronous trading hours across the diverse geographical locations of the exchanges (34). Markets in different time zones also close at different points in the day, so a shock occurring during U.S. trading hours does not appear in Asian markets' returns until the next opening day. This lag is expected in daily-return connectedness studies that span time zones and is accounted for directly by the QVAR model's lag

structure. After the data cleaning process, all indices are converted into logarithmic returns to ensure stationarity, a prerequisite for accurate connectedness estimation (35).

Furthermore, the study applies quantile-based measures that allow for the examination of risk transmission across the entire conditional distribution, moving beyond the limitations of traditional correlation-based models that often ignore tail-risk dependencies (36). The study combines two innovative methodologies like Quantile Vector Autoregression (QVAR) approach and the frequency domain connectedness decomposition (17, 18). This integrated approach fundamentally helps to eliminate the restriction to the conditional mean as well as the inability to distinguish between the short-run and long-run transmission channels. The study starts with a Quantile VAR framework.

A standard VAR model of order p for a K -dimensional vector of return series $y_t = (y_{1t}, y_{2t}, \dots, y_{Kt})'$ takes the form, as given in Equation [1]:

$$y_t = c + \sum_{i=1}^p A_i y_{t-i} + \varepsilon_t \quad [1]$$

where c is a vector of constants, A_i are $K \times K$ coefficient matrices and ε_t is a vector of error terms. The critical limitation of this standard formulation is that the coefficient matrices A_i are estimated at the conditional mean, capturing only average behaviour and remaining entirely silent on the dynamics prevailing during extreme market episodes.

Following Wold's theorem, the QVAR model is transformed into its infinite-order Quantile Vector Moving Average (QVMA) representation. This employs the model into Equation [2]:

$$Y_t = \mu(\tau) + \sum_{i=0}^{\infty} \phi_i(\tau) \varepsilon_{t-i} \quad [2]$$

Furthermore, H-step-ahead Generalised Forecast Error Variance Decomposition (GFEVD) is computed using the Equation [3] (37, 38):

$$\tilde{\Phi}_{ij}^{\tau}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h(\tau) \Sigma(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h(\tau) \Sigma(\tau) B_h(\tau)' e_i)} \quad [3]$$

Which explains GFEVD at quantile τ gives the fraction of the H -step-ahead forecast error variance of variable i attributable to shocks originating in variable j . Each row of the GFEVD is normalised to sum to unity as employed in Equation [4]:

$$\tilde{\Phi}_{ij}^{\tau}(H) = \frac{\tilde{\Phi}_{ij}^{\tau}(H)}{\sum_{j=1}^K \tilde{\Phi}_{ij}^{\tau}(H)} \quad [4]$$

Shocks originating in any one variable are transmitted more widely and more intensely across the markets. The directional TO connectedness of variable i measures the total shock contribution that variable i transmits to all other markets j , as given in Equation [5]:

$$C_{(i \text{ to } j)}^{\tau}(H) = \sum_{(i=1, j \neq i)}^K \tilde{\Phi}_{ij}^{\tau}(H) \quad [5]$$

The directional FROM connectedness of variable i measures the total spillovers that variable i receives from all other variables, as shown in Equation [6]:

$$C_{i \text{ from } j}^{\tau}(H) = \sum_{j \neq i, i=1}^K \tilde{\Phi}_{ij}^{\tau}(H) \quad [6]$$

The Net connectedness of each variable is then defined as the difference between its TO and FROM spillovers, as expressed in Equation [7].

$$NET_i^T = C_{(itoj)}^T(H) - C_{(ifromj)}^T(H) \quad [7]$$

If the NET_i^T is greater than 0, series is considered as net transmitter. While NET_i^T is less than 0, it is treated as a net receiver. The overall degree of interdependence across the market (Total Connectedness Index) is measured by Equation [8]:

$$TCI(H) = K^{-1} \sum_{i=1}^K TO_i(H) = K^{-1} \sum_{i=1}^K FROM_i(H) \quad [8]$$

The TCI value reflects how the average shocks of one market affect the rest of the markets (39). In addition, a higher TCI indicates greater market risk. Now the study shifts from a time-domain connectedness measure to a frequency-oriented connectedness evaluation. The frequency-domain representation of the QVMA process is obtained through the frequency response function (40).

$\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h$, Ψ_h denotes the moving average coefficient, $i = \sqrt{-1}$ is the imaginary unit and ω represents the frequency part. The spectral density at x_t is obtained as the Fourier transformation of the covariance structure of the QVMA process, as given in Equation [9]:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x_{t-h}') e^{-i\omega h} = \Psi(e^{-i\omega}) \Sigma \Psi'(e^{i\omega}) \quad [9]$$

While the frequency response function captures the transmission of shocks across frequencies, the spectral density matrix measures how the variance of the system is distributed over different frequencies. The frequency domain generalised forecast error variance decomposition (GFEVD) and normalised equations are presented in Equations [10, 11]:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} \left| \sum_{h=0}^{\infty} (\psi_h(\tau) e^{-i\omega h} \Sigma(\tau))_{ij} \right|^2}{\sum_{h=0}^{\infty} (\psi_h(\tau) e^{-i\omega h} \Sigma(\tau) \psi_h'(\tau) e^{i\omega h})_{ii}} \quad [10]$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^N \theta_{ik}(\omega)} \quad [11]$$

The frequency connectedness function measures the contribution of shocks originating from market j to the forecast error variance of market i at a specific frequency ω . $\theta_{ij}(\omega)$ quantifies the strength of connectedness between markets across different investment horizons. To ensure comparability across markets, the frequency connectedness function is normalized, as given in

Equation 11 by the row sum of the variance decomposition matrix. While $\tilde{\theta}_{ij}(\omega)$ measures connectedness at a specific frequency ω , investors are generally interested in connectedness over broader investment horizons rather than at a single frequency.

Therefore, the normalized frequency connectedness is aggregated over a predefined frequency $d = (a, b)$, where $a, b \in (-\pi, \pi)$ and $a < b$, as given in Equation [12]:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(\omega) d\omega \quad [12]$$

This aggregation facilitates the decomposition of connectedness into short-run and long-run components. Based on the frequency connectedness, directional connectedness measures are computed to quantify the transmission and reception of shocks across markets. The equation that explains the Net Pairwise Directional Connectedness is given in Equation [13]:

$$NPDC_{ij}(d) = \tilde{\theta}_{ij}(d) - \tilde{\theta}_{ji}(d) \quad [13]$$

The directional connectedness measures quantify the spillovers transmitted to and received from the rest of the markets. For a market i to j , If the NPDC is less than zero, it indicates that the latent market exerts a greater influence on the former, rather than vice versa, as given in Equation [14]:

$$TO_i(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(d) \quad [14]$$

Similarly, $FROM_i(d)$ measures the amount of shock market i received from the rest of the markets is represented by Equations [15, 16]:

$$FROM_i(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}(d) \quad [15]$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \quad [16]$$

Equation 16 derives the net connectedness measure. This is obtained as the difference between TO and FROM connectedness and determines whether a market is a net transmitter or net receiver of shocks. Finally, the Total Connectedness Index (TCI) summarises the overall level of connectedness within the system. It's given in the Equation [17]:

$$TCI(d) = N^{-1} \sum_{i=1}^N TO_i(d) = N^{-1} \sum_{i=1}^N FROM_i(d) \quad [17]$$

Results and Discussion

The section begins by discussing the return series plots of the 4 key automobile market players and the global oil market, as presented in Figure 2. It is observed that there is an absence of systemic trend, as all the return series fluctuate around a mean close to zero. However, it reveals a period of volatility clustering. This suggests the presence of time-varying volatility. Notably, a sharp spike is visible in every series during early 2020 because of the COVID-19 outbreak. This disrupts global

production networks, supply chains and investor sentiment. The USA and Japanese automobile markets show a frequent volatile nature, especially when the market experiences uncertainties. At the same time, the Indian automobile market appears comparatively less volatile outside major crisis episodes. To understand the spillover between these markets in extreme situations, the study must employ a QVAR connectedness estimation.

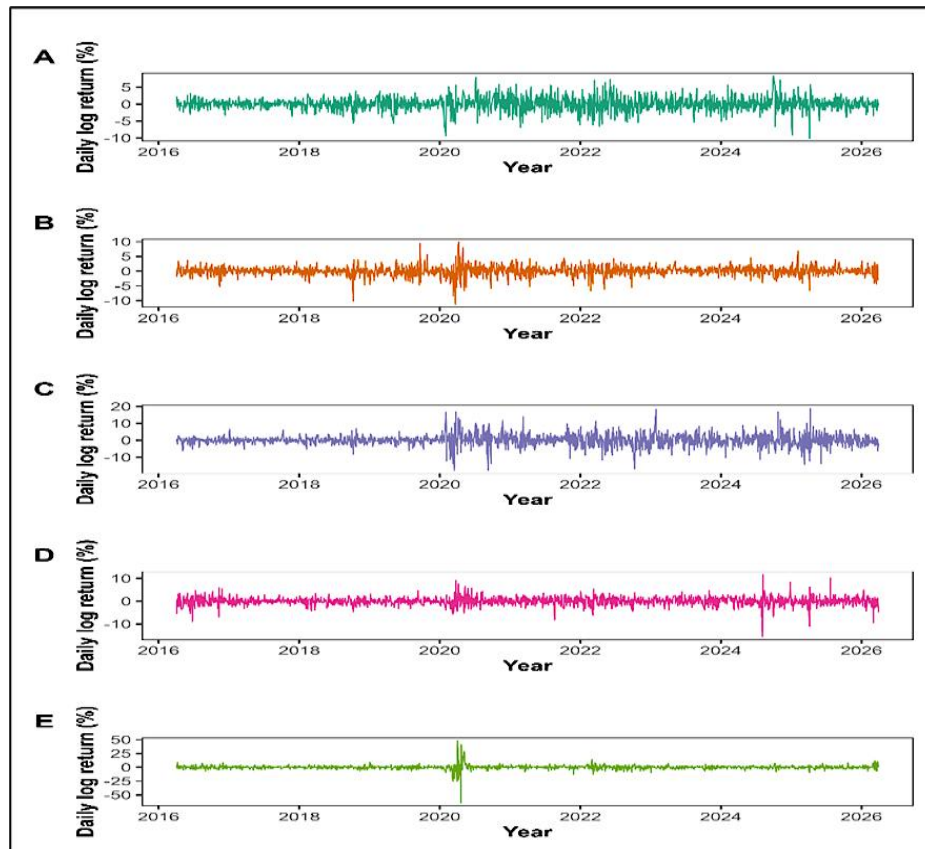


Figure 2: Return Series Plot of the Oil and Automobile Market. (A) China, (B) India, (C) USA, (D) Japan, (E) Oil

The descriptive statistics given in Table 1 summarise the return characteristics of the automobile sector indices and the crude oil market. The mean returns are positive across all five markets, with China recording the lowest average return and the United States exhibiting the highest. In terms of volatility, the U.S. automobile market is the most volatile among the four automobile markets, with a standard deviation of 3.14. However, the crude oil market exhibits the highest overall volatility with a standard deviation of 3.48, surpassing all the other markets. The oil market also records the wide range of fluctuation from -64.37 to 48.57. This extreme fluctuation is because of the unprecedented turmoil in the global energy market during the COVID-19 pandemic. In particular, the historic collapse in crude oil prices in April 2020 resulted in price movements that had not been observed over the previous two decades. Notably, all the markets are negatively skewed,

suggesting downside risk is more significant than positive gains. All the Kurtosis values above 3 indicate a leptokurtic distribution with fat tails. Furthermore, the oil market marked a Kurtosis Value of 92.3, showing extreme movement during the sample period. Among the equity indices, Japan records the highest kurtosis [11.138], followed by India [9.929], the USA [8.714], and China [5.922]. The Jarque–Bera statistics are significant at the level. Overall, the result highlights that the return distributions are non-normal, asymmetric and existence of tail risk. This provides a base for bringing a quantile-based connectedness framework, as mean-based approaches may fail to capture the heterogeneous transmission of shocks across different market Conditions. Also, the Quantile Vector Autoregression (QVAR) model captures the dynamic interdependence among variables across different quantiles of the conditional return distribution.

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	JB_Stat	JB_Pvalue
China	0.017498	1.784215	-10.088	8.374649	-0.08287	5.922324	748.9375	<0.01
India	0.049524	1.515319	-11.3101	9.899663	-0.39135	9.929463	4251.08	<0.01
USA	0.089292	3.141088	-17.878	18.96405	-0.05583	8.713657	2854.883	<0.01
Japan	0.031252	1.700451	-15.6152	11.8112	-0.38368	11.13784	5840.6	<0.01
Oil	0.052488	3.477828	-64.3699	48.5662	-1.34652	92.38843	699118.6	<0.01

Note: SD = Standard Deviation, Min = Minimum, Max = Maximum, JB = Jarque Bera statistics.

Before initiating the QVAR estimation model, the stationarity test was conducted. The study applied the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for this and highlighted them in Table 2. The ADF and PP Statistics are significant. These findings indicate that all the variables reject

the presence of a unit root and conclude that the variables are stationary in level. Furthermore, the KPSS statistics are small, and their p-value for all the variables are 0.1. This leads to an inference of failure to reject the null hypothesis of stationarity for every series.

Table 2: Stationarity Test

Variables	ADF Statistic	PP α Statistics	KPSS Statistic
China	-12.051***	-1903.400***	0.048
India	-11.905***	-2134.700***	0.169
USA	-11.759***	-2178.300***	0.068
Japan	-13.918***	-2101.300***	0.040
Oil	-11.428***	-2078.100***	0.044

Note: ADF = Augmented Dickey–Fuller; PP = Phillips–Perron α statistics and KPSS = Kwiatkowski–Phillips–Schmidt–Shin. *** denotes statistical significance at the 1% level. The null hypothesis for the ADF and PP tests is the presence of a unit root, whereas the null hypothesis for the KPSS test is stationarity.

Time-domain Connectedness

After the confirmation of stationarity, Tables 3-5 highlight the static connectedness result at the lower tail, median tail and upper tail. A clear asymmetry emerges across the return distribution. The Total Connectedness Index (TCI) is 68.65% in

the lower tail ($\theta=0.05$) and 67.96% ($\theta=0.95$) in the upper tail, whereas the value declines to 10.77% at the median quantile ($\theta=0.5$). Similar patterns are visible for the corrected Total Connectedness Index (cTCI), during the bearish and bullish market

conditions, the values reach 85.81% and 84.94%, respectively. Whereas under normal market conditions, it is 13.46%. The study on the logistics market across 17 countries shows the same pattern, where extreme events increase connectedness over normal market conditions (41). A comparable gap during extreme events and normal market conditions is identified in the commodity market study. At extreme quantiles, the connectedness level reaches at 74-75%, but in normal conditions it is valued at 18.57% (42). Our results clearly depict the difference in connectedness across quantiles. That is, during normal market conditions, interconnectedness among the automobile sectors and the oil market is weak. Whereas stronger cross-market linkages are present in extreme conditions. Suggesting that market participants respond more synchronously during these conditions. Also, the TO and FROM transmission values in the upper and lower tails are higher than the average condition. Notably, the

US automobile sector acts as the net transmitter of shock across all market conditions, with NET values of 3.80, 4.75 and 2.28 at the lower, median and upper quantiles respectively. This finding suggests that the shock originating in the USA is spilling over to the rest of the markets. The oil market shows a contrasting pattern. Oil acts as the largest net receiver of shocks during the bearish market condition with a significant value of -7.24. This value further drops to -7.93 when the market is in bullish condition. Nevertheless, during the normal market, they act as the net transmitter along with the US market. This same pattern is visible in international logistics markets. The US market acts as the transmitter and Asian economies as net receivers (41). Oil's role as a receiver also holds in gold and equity markets (43). These findings come to a point of strong asymmetric spillover and highlight the importance of analysing the interconnectedness across different market conditions.

Table 3: Lower Tail Connectedness ($\theta=0.05$)

	China	India	USA	Japan	Oil	FROM
China	30.95	18.41	18.49	18.02	14.13	69.05
India	18.08	29.39	18.7	19.32	14.51	70.61
USA	17.61	18.33	31.22	17.85	14.99	68.78
Japan	17.66	19.63	18.38	30.2	14.13	69.8
Oil	16.18	15.9	17.01	15.92	34.99	65.01
TO	69.54	72.26	72.58	71.12	57.77	343.26
Inc.Own	100.49	101.65	103.8	101.31	92.76	cTCI/TCI
NET	0.49	1.65	3.8	1.31	-7.24	85.81/68.65
NPT	1	3	4	2	0	

Note: TCI = Total Connectedness Index, cTCI = Corrected Total Connectedness Index, TO = total directional connectedness to others, FROM = Total Directional Connectedness from Others, NET = Net Directional Connectedness, Inc.Own = Own-market Contribution Including Spillovers, NPT = Net Pairwise Transmission.

Table 4: Median Tail Connectedness ($\theta=0.5$)

	China	India	USA	Japan	Oil	FROM
China	91.31	2.65	2.91	2.58	0.55	8.69
India	2.45	84.83	4.95	7.37	0.4	15.17
USA	2.14	3.74	90.1	2.55	1.47	9.9
Japan	2.53	7.32	5.22	83.36	1.56	16.64
Oil	0.87	0.34	1.57	0.66	96.56	3.44
TO	7.99	14.05	14.66	13.17	3.98	53.85
Inc.Own	99.29	98.88	104.75	96.53	100.54	cTCI/TCI
NET	-0.71	-1.12	4.75	-3.47	0.54	13.46/10.77
NPT	1	1	4	2	2	

Note: TCI = Total Connectedness Index, cTCI = Corrected Total Connectedness Index, TO = total directional connectedness to others, FROM = Total Directional Connectedness from Others, NET = Net Directional Connectedness, Inc.Own = Own-market Contribution Including Spillovers, NPT = Net Pairwise Transmission.

Table 5: Upper Tail Connectedness ($\theta=0.95$)

	China	India	USA	Japan	Oil	FROM
China	31.23	18.24	18.25	18.01	14.27	68.77
India	18.12	31.01	18.25	19.17	13.45	68.99
USA	18.13	18.31	31.32	17.56	14.67	68.68
Japan	18.12	19.27	17.7	30.94	13.96	69.06
Oil	16.4	15.47	16.76	15.65	35.72	64.28
TO	70.77	71.3	70.96	70.4	56.35	339.78
Inc.Own	101.99	102.31	102.28	101.34	92.07	cTCI/TCI
NET	1.99	2.31	2.28	1.34	-7.93	84.94/67.96
NPT	2	4	3	1	0	

Note: TCI = Total Connectedness Index, cTCI = Corrected Total Connectedness Index, TO = total directional connectedness to others, FROM = Total Directional Connectedness from Others, NET = Net Directional Connectedness, Inc.Own = Own-market Contribution Including Spillovers, NPT = Net Pairwise Transmission.

The above result provides the average connectedness over the entire sample period, still they lack to reveal the interconnectedness evolve through time. So that we have to address the dynamic nature of the shocks across the years. For that we plot dynamic total connectedness plot and Net directional spillover plot for the lower quartile ($\theta = 0.05$), median quartile ($\theta = 0.5$) and the upper quartile ($\theta = 0.95$). These plots provide a clear picture of the asymmetric connectedness that happens during the turmoil period. Figure 3 shows the dynamic TCI plot. In the lower quartile, the value varies between 65% and 78%. A similar pattern is showing in the upper quartile ($\theta = 0.95$) as well with value ranges between 65% to 75%.

This explains that adverse positive and adverse negative shocks are transmitted across the market. Nevertheless, the average market condition (median quartile $\theta = 0.5$) ranges between 10% to 30%. This exhibits a lower level of connectedness between the markets. The increase is observed during the early 2020s because of COVID-19. A similar movement pattern during the pandemic is also evident in earlier studies (41, 43). Gradually the connectedness has decreased and remains relatively subdued compared with the tail quantiles. This behaviour suggests that under normal market conditions, market-specific information dominates cross-market influences.

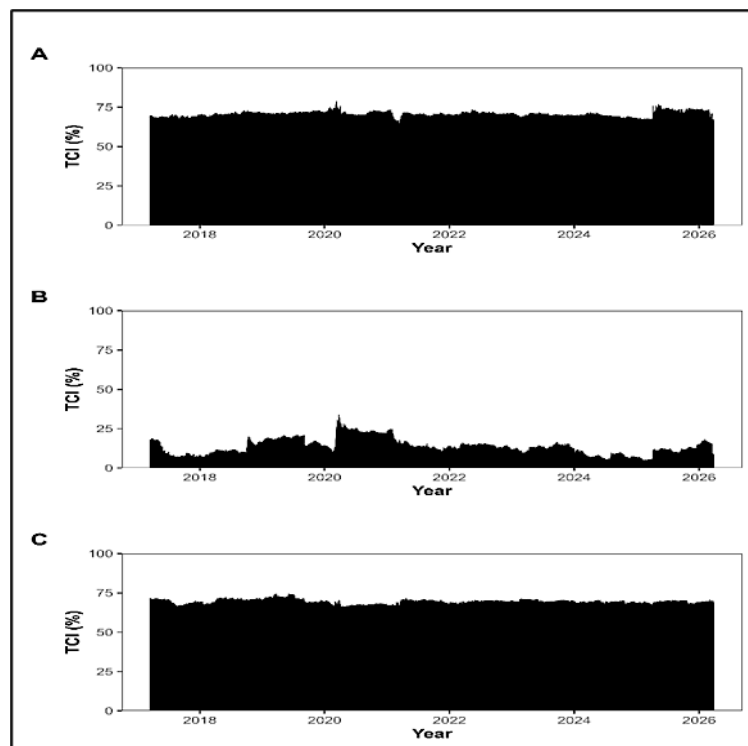


Figure 3: TCI Plot. (A) Lower Tail ($\tau = 0.05$), (B) Median Tail ($\tau = 0.5$), (C) Upper Tail ($\tau = 0.95$)

Although the Dynamic Total Connectedness plot captures the overall magnitude of spillovers within the system, it does not reveal the direction of shock transmission among markets. The TCI plot lacks the ability to distinguish between transmitters and absorbers in the market. To address this limitation, the study plots a dynamic net directional connectedness plot. This measure provides information on the time-varying roles of individual markets within the connectedness network. This helps to identify the transmitter and the receiver across the year. Figure 4 presents the Net directional connectedness under the bearish market conditions. Although none of the markets can be classified as a persistent net receiver or net transmitter over the entire sample period, the U.S. automobile market predominantly records positive net connectedness values, implying a stronger tendency to transmit shocks to other markets. Conversely, the global crude oil market exhibits mostly negative net connectedness values, indicating that it primarily receives spillovers from the automobile markets. In comparison, the automobile markets of China, India and Japan exhibit more time-varying and dynamic connectedness patterns, frequently switching

between net transmitter and net receiver roles across different periods. They are switching their role of transmitter and receiver throughout the period. This indicates that these markets are highly dependent on prevailing market conditions and regional economic developments. Nevertheless, India displays several prolonged periods of positive net connectedness, playing a stronger transmitting role compared with China and Japan. Figure 5 reveals the Net directional connectedness for the median tail ($\theta = 0.5$). It is clearly evident that US Automobile market is the principal net transmitter. This suggests that shocks originating from the US market have a greater influence on the other markets during normal market conditions. Additionally, India and Japan predominate with negative connectedness values, claiming that both markets are net receivers during the normal period. Chinese and oil markets showed a balanced pattern, but it is notable that during 2020 and 2022, the Chinese market faced a negative connectedness. Collectively, the normal market conditions witnessed a more centralised spillover structure in which the U.S. automobile sector serves as the primary source of risk transmission.

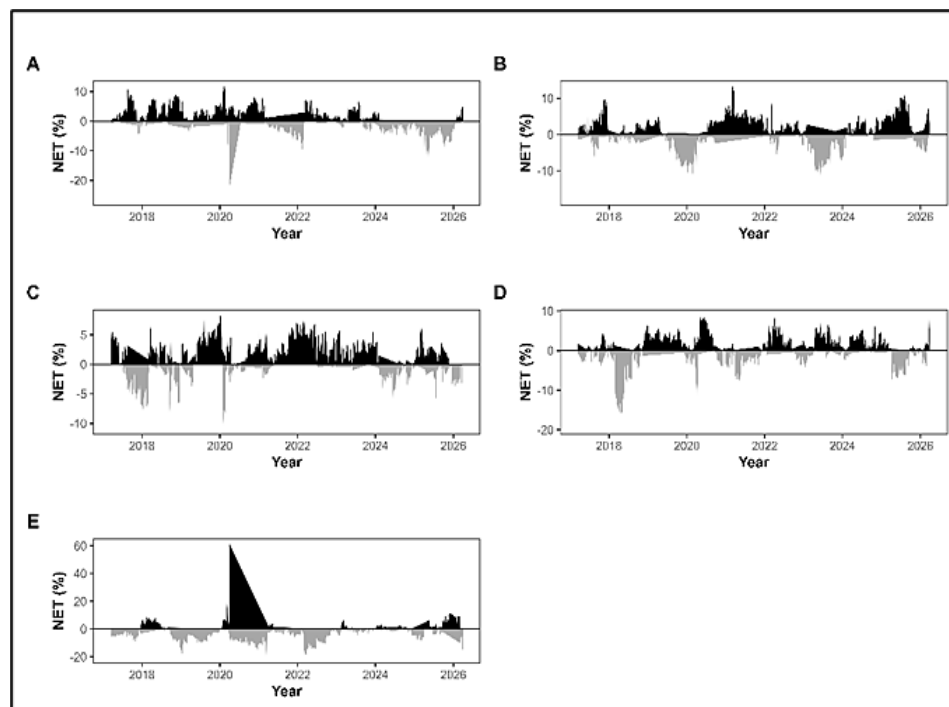


Figure 4: Net Directional Spillover Plot ($\theta = 0.05$). (A) China, (B) India, (C) USA, (D) Japan, (E) Oil

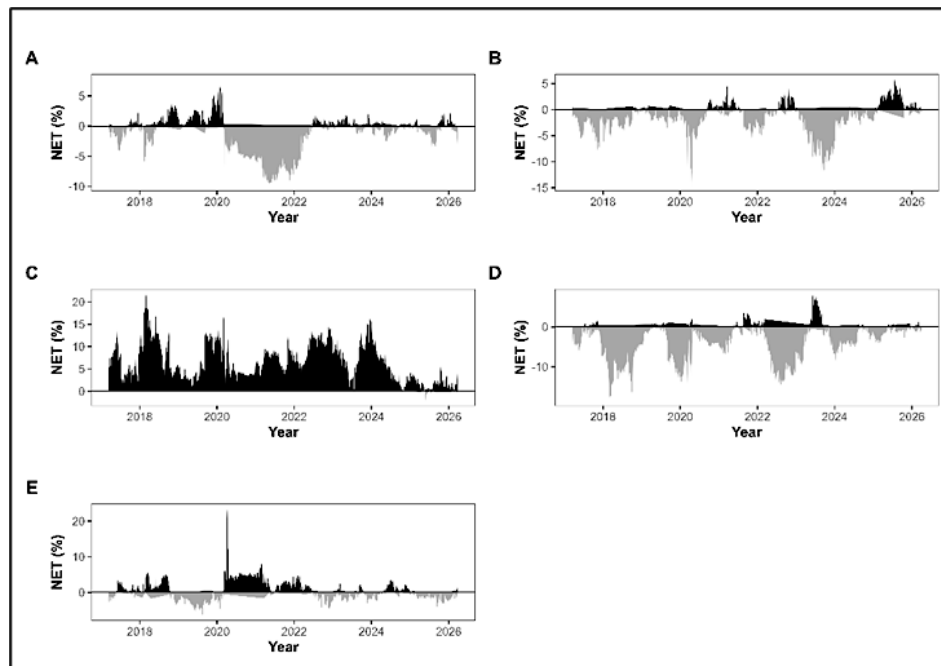


Figure 5: Net Directional Spillover plot ($\theta = 0.5$). (A) China, (B) India, (C) USA, (D) Japan, (E) Oil

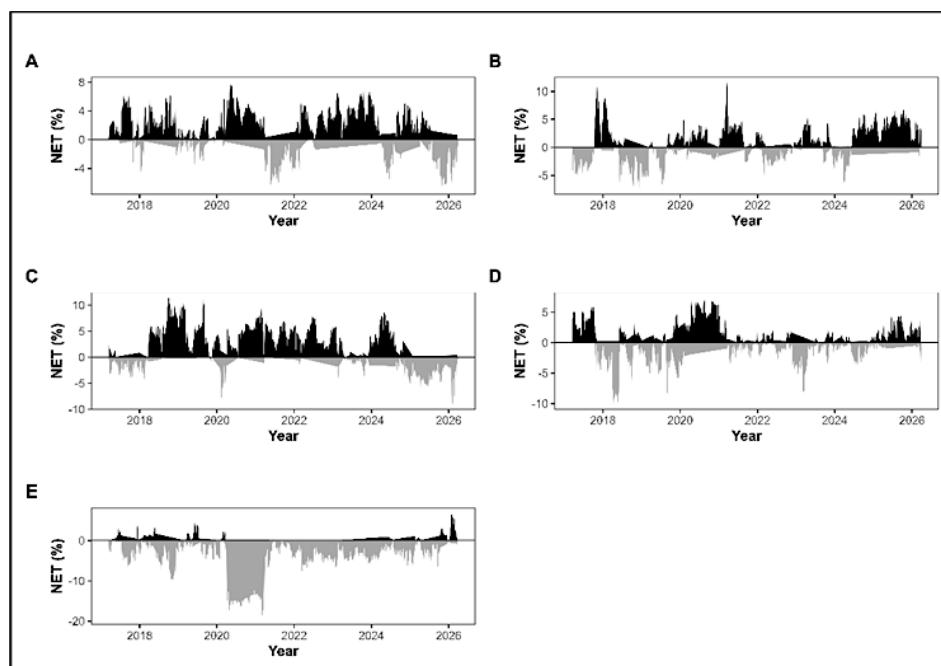


Figure 6: Net Directional Spillover Plot ($\theta = 0.95$). (A) China, (B) India, (C) USA, (D) Japan, (E) Oil

Figure 6 highlights the net directional connectedness at the positive extreme ($\theta = 0.95$). The results show a sizable reconfigured spillover pattern compared to the lower and median tails. The USA market played a prominent role as a net transmitter in the lower and median tails, while in the upper extreme tails, its dominance has weakened. However, India and China have become prominent net transmitters while Japan exhibits a

more balanced role by alternating between a transmitter and receiver during this period. It is evident that the oil market has become a net recipient from the automobile market. Under positive extreme market conditions, spillover transmission becomes increasingly concentrated within the automobile sectors themselves. Comparing the three quantiles reveals significant asymmetry in the connectedness. The lower tails

show the strongest spillover transmission, indicating heightened contagion during adverse market conditions. During normal condition, the connectedness become weak. whereas the upper-tail is characterized by a redistribution of spillover leadership among automobile markets.

Frequency-domain Connectedness

Earlier, we discussed the overall magnitude and direction of connectedness among automobile markets. However, they overlooked the short- and long-term parts of the connectedness. In particular, shocks may be transmitted over a short horizon due to market sentiments or have a long-lasting effect through persistent economic and financial linkages. To distinguish between these two effects, the connectedness measures are decomposed into short-run (1–5 days) and long-run (beyond 5 days) frequency components. This helps to understand

the nature of spillover, whether it is transitory or persistent and it is presented in Table 6. The values shown in parentheses are the short-term and long-term frequency connectedness, respectively. The total connectedness index (TCI) value is 13.80%. This indicates a relatively low connectedness between the automobile- oil market network. It has to be highlighted that the short-run TCI is 10.6% while the long run contributes only 3.20%. The result suggests that information transmission among the markets occurs primarily over shorter horizons and that most shocks dissipate relatively quickly. Additionally, market-specific factors remain the primary source of return variation. If we look at the NET part of Table 6, the U.S. automobile sector is the leading transmitter across both short- and long-run frequencies. Japan and India are consistent receivers of shocks originating from other markets in both frequencies.

Table 6: Frequency Connectedness Result

	China	India	USA	Japan	Oil	FROM
China	87.03 (70.26, 16.77)	3.20 (2.55, 0.65)	3.71 (2.55, 1.1)	4.58 (3.78, 0.8)	1.49 (1.25, 0.24)	12.97 (10.18, 2.79)
India	3.07 (2.51, 0.56)	83.24 (67.12, 16.11)	5.29 (3.62, 1.67)	7.07 (5.41, 1.66)	1.33 (0.96, 0.36)	16.76 (12.51, 4.25)
USA	2.49 (2.05, 0.44)	3.82 (3.09, 0.74)	88.2 (71.69, 16.51)	3.65 (3.05, 0.6)	1.83 (1.50, 0.32)	11.80 (9.69, 2.11)
Japan	4.16 (3.25, 0.91)	6.55 (5.13, 1.42)	7.28 (4.99, 2.3)	79.42 (64.69, 14.73)	2.58 (1.89, 0.69)	20.58 (15.27, 5.31)
Oil	1.92 (1.33, 0.58)	1.52 (1.24, 0.28)	1.96 (1.60, 0.36)	1.47 (1.16, 0.31)	93.13 (75.48, 17.65)	6.87 (5.33, 1.54)
TO	11.64 (9.15, 2.5)	15.09 (12.01, 3.08)	18.25 (12.82, 5.43)	16.78 (13.39, 3.38)	7.23 (5.61, 1.62)	68.98 (52.98, 16)
Inc.Own	98.67 (79.40, 19.27)	98.33 (79.14, 19.19)	106.45 (84.51, 21.94)	96.20 (78.08, 18.12)	100.36 (81.1, 19.26)	cTCI/TCI 17.24/13.8
NET	-1.33 (-1.03, -0.3)	-1.67 (-0.5, -1.17)	6.45 (3.13, 3.32)	-3.8 (-1.87, -1.93)	0.36 (0.28, 0.08)	13.24/10.6, 4/3.2
NPT	1 (1,2)	2 (2,1)	4 (4,4)	2 (2,1)	1 (1,2)	-

Note: “The model used a 200-day rolling window Q-VAR model with lag order 1(BIC) with a 100-step-ahead generalized forecast error variance decomposition”. The values in the parentheses () represent the short- and long-term frequency connectedness, while the other values are in time measures. TCI = Total Connectedness Index, cTCI = Corrected Total Connectedness Index, NPT = Net Pairwise Transmission.

Figure 7 shows the dynamic frequency median TCI plot and reveals more substantial information than the Table 6 results. The total connectedness index fluctuates between a range of 5% and 35%. This shows the inconsistency of the spillover throughout the sample period. The highest TCI value is observed only in early 2020, due to intense uncertainty in global financial and commodity market, the unprecedented COVID-19 outbreak. where all the 3 TCI values peaked during that time

period. After that event, the TCI value showed a downward trend. We could see a fall in value from 35% (2020) to 5% (2025). It is also noticeable that in early 2026, the trend changed to an upward movement, and the value peaked around 15- 17% in the short run and total TCI due to the ongoing USA-IRAN war. The short-run component closely follows the movement of the total connectedness index and exhibits significant increases during periods of market stress. The long run shows

relatively low connectedness with total connectedness. Their contribution to the total market connectedness is considerably smaller than that of the short run. These outputs are in line with earlier static results of Table 6. Overall, the output shows that short-run components are the major frontrunner for the total TCI in the automobile-oil network. This information plays a

significant role for crucial investors and risk managers because a major shift in the long-term TCI will bring a significant change in the market structure (44). The segregation of TCI into three dynamics not only improves explainability but also highlights the superiority of QVAR while handling the outliers. The overall result aligns with the outputs of past research (39).

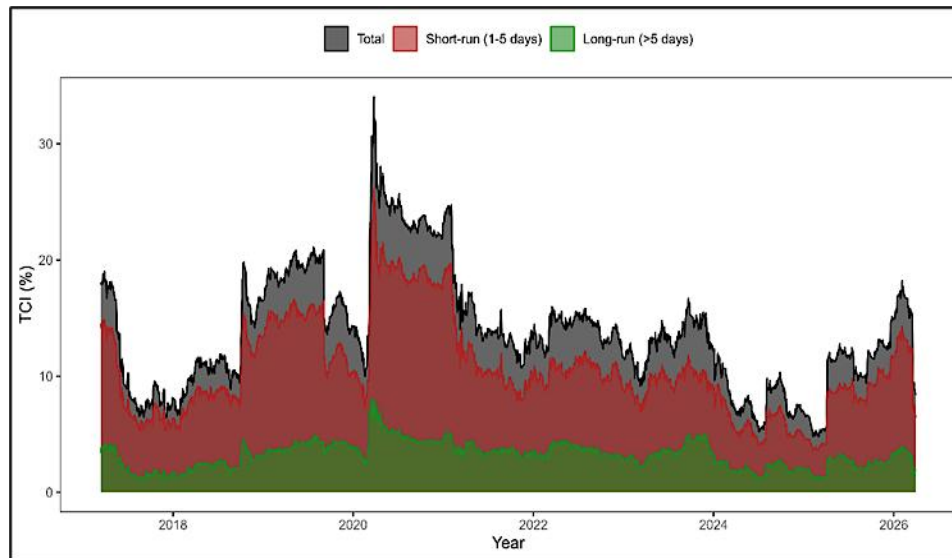


Figure 7: Median TCI Frequency Connectedness Plot

Figure 8 presents the Net Directional Connectedness results under the frequency domain in different colours like black, red and green. Black represents the total NET dynamic, whereas red and green represent the short- and long-term dynamics, respectively. The major finding is that the US automobile market is primarily a transmitter of shocks throughout long-term dynamics, but due to the short-term dynamics, they act as a receiver for a temporal period. In contrast, even though Japan exhibits a negative net connectedness position across most of the period

and they act as the receiver. But for a limited period, they act as a transmitter due to the short-term dynamics. Hence, the long-term dynamics show consistency as either a receiver or transmitter. While the short-term dynamics are either getting more intense or weaker net transmission power, either absorbing or sending it. Therefore, separating short-run and long-run connectedness provides a more comprehensive understanding of how shocks propagate across global automobile and oil markets.

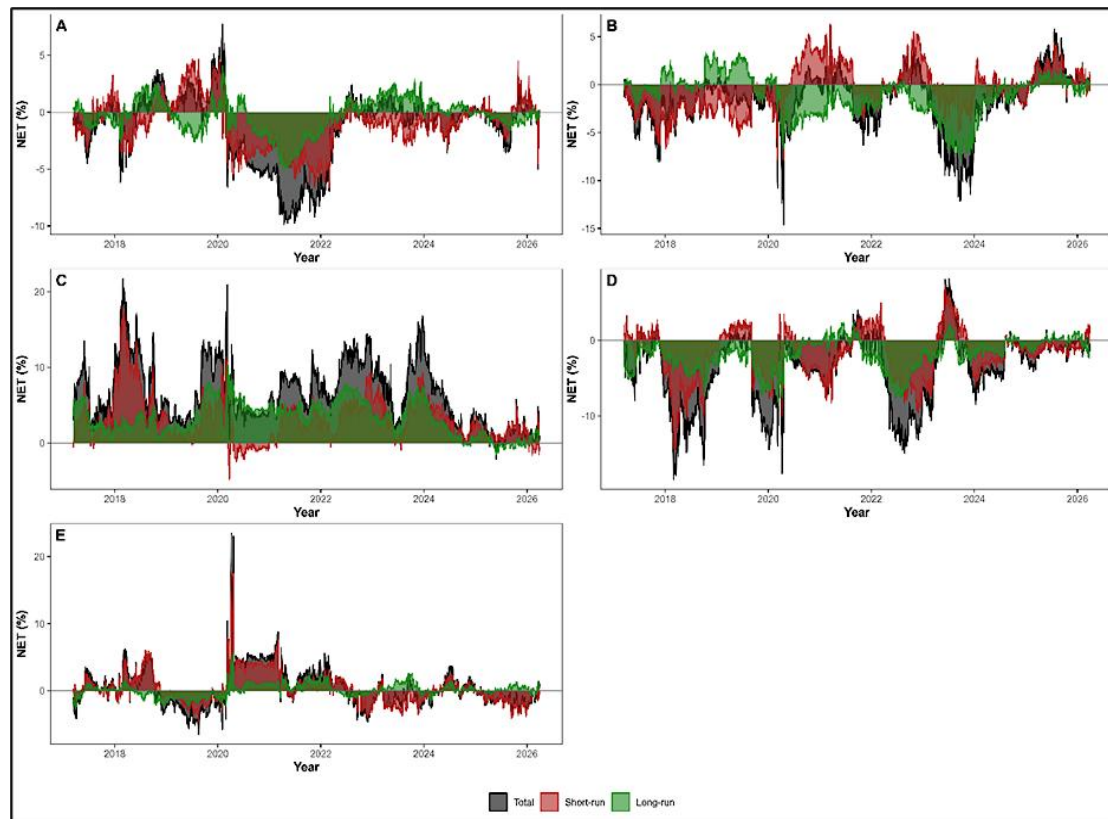


Figure 8: Frequency-based NET Directional Connectedness Results). (A) China, (B) India, (C) USA, (D) Japan, (E) Oil

Conclusion

This study applies the time-frequency quantile connectedness among the automobile sectors of China, India, the USA, Japan and the global oil market. Based on analysing the daily return data over the period April 2016 to March 2026, the study realised that the degree of shock transmission or spillover effect across the markets depends on the different market conditions. Particularly, both the upper and lower tails have greater TCI values than the conditional median, driving significant cross-market interconnectedness during extreme market conditions. This indicates that the market responds more synchronously during stress conditions, whereas during normal market conditions, the shocks are more market specific. Understanding this tail dependency helps the crucial investors and risk managers in decision making. This paper contributes to the existing literature by extending the connectedness analysis into a short run, long run quantile frequency domain. The result claims that the short run and long run move in similar direction. Nonetheless, the short run dynamics are the prime reason for change in the total frequency domain. Furthermore, the directional connected-

ness under frequency domain reveals that the role of each market is not constant. Every market act as a transmitter as well as a receiver at some point in its time horizon. Overall, this study contributes to the growing literature on financial connectedness by showing the nexus between the automobile and oil markets is featured by asymmetric, state-dependent and highly short-run spillover dynamics. These findings highlight the importance of considering both market conditions and investment horizons when evaluating systemic risk, portfolio diversification opportunities and the transmission of shocks across globally integrated markets. The study also has certain limitations. The study considers only the top four major automobile producers, so the findings cannot be generalised to other automobile-producing regions such as Germany, France and Spain, which operate within a more integrated European market. The study applied Brent price as the global oil benchmark. Other crude oil price grades, such as West Texas Intermediate (WTI), can move differently from Brent under certain market conditions. The frequency-domain analysis splits connectedness into just two bands, short-run and

long-run, so it does not look at horizons in between.

For future research, the study may incorporate European markets as well to get a comprehensive understanding of the overall global vehicle market and explore emerging segments within the mobility domain, such as the electric vehicle index and its nexus with oil and battery metals. Addition of Wavelet Quantile Coherence (WQC) helps to gain deeper comprehension of time- and frequency-based connectedness.

Abbreviations

GFC: Global Financial Crisis, GFEVD: Generalized Forecast Error Variance Decomposition, NPDC: Net Pairwise Directional Connectedness, QVAR: Quantile Vector Autoregression, QVMA: Quantile Vector Moving Average, TCI: Total Connectedness Index, VAR: Vector Autoregression.

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Author Contributions

Althaf K Umar: Conceptualization, Data Curation, Formal Analysis, Software, Visualization, Investigation, Writing – Original Draft, Writing – Review and Editing, Muthumeenakshi M: Conceptualization, Methodology, Supervision, Validation, Interpretation of Results, Writing – Critical Review and Final Editing. All authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Data Availability

All the data used in the study are publicly available. The data used for this study will be provided from the corresponding author upon request.

Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of generative AI to assist in the paraphrasing of certain parts of the manuscript. All content generated through AI was critically reviewed, edited and verified by the authors to ensure accuracy, originality and compliance with academic standards. The authors take full responsibility for the integrity and validity of the manuscript.

Ethics Approval

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