10.48047/jocaaa.2024.33.06.153

GLOBAL FINANCIAL INTEGRATION: VOLATILITY AND RETURN SPILLOVERS FROM DEVELOPED TO EMERGING MARKETS IN THE POST-PANDEMIC ERA

Mr. Rahul Moolbharathi[1],Dr.Yatheesh Chandra M.S[2]
Research Scholar, Department of Management Studies, VTU CPGS, Kalaburagi
Associate Professor, Department of Management Studies, VTU CPGS, Kalaburagi
rahulsm.vtu@gmail.com&yathishchandra18@gmail.com

Abstract
traditionally, developed markets (DMs) have generated volatility and return spillovers, channeling risks and shocks into emerging markets (EMs), which demonstrated weaker resilience and heightened sensitivity. The COVID-19 crisis reversed these roles, making developing countries significant exporters of financial market risk, while developed countries exhibited increased risk absorption. The risk spillover levels of developing countries rose rapidly during major outbreak periods, whereas developed markets' risk spillover decreased, suggesting their greater capacity to absorb shocks and act as "safe havens" for global capital flows. The research paper is focused in understanding the connectedness among of major developed (e.g., US, UK, Japan) and emerging (e.g., India, China, Brazil) markets throughout the pre-pandemic, pandemic, and post-pandemic phases. The data was called from year 2017-2024 and found that not all developed are net absorber and similarly all developing markets are not risk transmitter. The study helped to understand the behavior of developed market and emerging market during the pandemic situation.

Keyword: Risk and Return, volatility, Diebold and Yilmaz spillover index ,shock absorber.

INTRODUCTION

The COVID-19 pandemic significantly transformed the structure and magnitude of financial market spillovers, intensifying systemic risks and reshaping global interconnectedness. Prior to the outbreak, international financial markets were already integrated to a degree that allowed shocks in one region to affect others (Forbes & Rigobon, 2002; Diebold & Yilmaz, 2014). However, the pandemic accelerated these transmission channels, increasing both the speed and sensitivity with which volatility and return shocks spread across markets. Emerging markets (EMs) were disproportionately affected due to limited institutional strength, weaker risk-sharing mechanisms, and heightened exposure to global economic disturbances (Bekaert et al., 2014). As a result, local shocks rapidly escalated into global disruptions, underscoring structural vulnerabilities within financially constrained economies.

Understanding these dynamics requires robust spillover modelling, particularly for index return data. Such models help quantify how volatility originating in one market influences others, thereby mapping systemic risk propagation. During the pandemic, sector-level behaviour illustrated marked heterogeneity in shock transmission. Cyclical sectors such as money markets, energy, and oil & gas became major transmitters of instability, reflecting volatile demand conditions, supply chain bottlenecks, and severe commodity price fluctuations (Baumeister & Kilian, 2016; Devpura &

10.48047/jocaaa.2024.33.06.153

Narayan, 2020). These sectors intensified systemic stress by amplifying volatility across broader financial networks. In contrast, defensive sectors—most notably pharmaceuticals and healthcare—benefited from increased global demand for medical goods, demonstrating resilience and exhibiting favorable risk-adjusted returns (Ramelli & Wagner, 2020).

Geographical divergence also played a substantial role in shaping spillover outcomes. Latin American and North American markets experienced heightened contagion primarily due to their dependence on global trade and limited fiscal maneuverability during crisis periods (Corbet et al., 2020). Conversely, Asia (excluding China) exhibited relatively moderate vulnerability, supported by early containment efforts and diversified economic structures (Zhang et al., 2020). China's market dynamics remained distinct, influenced by strong policy interventions and stringent domestic regulatory measures.

Central to quantifying these cross-market influences is the Diebold and Yilmaz Spillover Index, which uses forecast error variance decompositions, derived from vector autoregressive (VAR) models to measure directional risk transmission. This framework highlighted substantial time-variability in spillover intensity during the pandemic. Periods marked by stringent containment policies corresponded with reduced spillover levels, whereas delayed responses allowed shocks to proliferate (Goodell, 2020).

Overall, the pandemic exposed critical gaps in EM financial infrastructure, including institutional fragility, limited investor confidence, and insufficient mechanisms for absorbing shocks. While developed markets (DMs) continued to attract global capital as relative safe havens, the crisis also demonstrated that no economy is insulated from systemic risks in an era of deep financial integration (Gormsen & Koijen, 2020). These insights emphasize the necessity of strengthening regulatory frameworks, enhancing cross-border coordination, and developing robust institutional buffers to increase resilience in future global crises.

REVIEW OF LITERATURE

A growing body of empirical research examines how COVID-19 altered global volatility and return spillovers. Li (2021) identifies asymmetric volatility transmission across major developed markets—namely the US, UK, Japan, France, and Germany—showing that spillovers increased sharply during the pandemic, particularly from developed to emerging economies. Corbet et al. (2020) extend this analysis by incorporating commodities such as oil and gold, demonstrating substantial contagion and increased interconnectedness triggered by pandemic-related uncertainty.

Studies focusing on emerging markets provide additional insights. Das (2022), analysing Indian financial markets, finds that sector-level spillovers intensified substantially during pandemic waves, creating abrupt surges in volatility transmission. Mensi et al. (2022) observe similar dynamics using intraday data from oil, gold, and the S&P 500, confirming heightened cross-asset contagion during the early phases of the pandemic.

Network-based research by Samitas et al. (2021) reveals rapid and widespread contagion across 51 global equity markets during lockdowns, including markets previously considered relatively isolated.

10.48047/jocaaa.2024.33.06.153

Complementary work by Tan et al. (2022) focusing on precious metals and energy commodities shows that the pandemic amplified volatility interdependence, with crude oil emerging as a dominant shock transmitter, while gold acted as a stabilising asset.

Sectoral spillovers have also received attention. Sahoo et al. (2024), utilising BEKK-GARCH and GO-GARCH frameworks across the US, UK, China, and India, report strong domestic volatility effects but also significant cross-market spillovers, particularly in IT, healthcare, and oil & gas sectors. Umar et al. (2021) highlight deeper linkages between emerging market equities and US government bonds during the pandemic, indicating increased cross-jurisdictional risk transmission.

Collectively, these studies confirm that COVID-19 induced higher spillover intensity, greater network density, and more complex interdependence patterns across international markets. They also underscore the critical need for dynamic modelling approaches that capture the time-varying and episodic nature of pandemic-driven contagion.

NEED OF THE STUDY

The unprecedented volatility triggered by COVID-19 reshaped financial interconnectedness across global markets. Understanding how shock transmission mechanisms evolved during this period is essential for investors, portfolio managers, policymakers, and regulators. Despite extensive research, gaps remain—particularly regarding region-specific and sector-specific spillovers across both developed and emerging markets after the pandemic. Moreover, limited attention has been given to comparative analyses spanning pre-pandemic, pandemic, and post-pandemic phases. Addressing these gaps is critical for developing risk-mitigation strategies, strengthening policy design, and enhancing resilience in periods of systemic uncertainty.

Scope of the Study

This study investigates volatility and return spillovers across major developed markets (e.g., the US, UK, Japan) and key emerging markets (e.g., India, China, Brazil) over three distinct phases: pre-pandemic, pandemic, and post-pandemic. The scope includes:

- A comparative analysis of risk-transmission mechanisms across regions and sectors.
- An assessment of contagion intensity during extreme events such as pandemic waves.
- Evaluation of directional spillovers to identify risk transmitters and receivers.
- Examination of sectoral asymmetries in volatility propagation.

This integrated scope facilitates a comprehensive understanding of evolving financial interconnectedness in a post-COVID global environment.

10.48047/jocaaa.2024.33.06.153

OBJECTIVES OF THE STUDY

1. To identify the direction and asymmetry of spillover effects between developed and emerging market indices.
2. To investigate how spillover intensities fluctuate during systemic shocks such as the COVID-19 pandemic.
3. To evaluate the process of developed versus emerging markets as net risk transmitters or absorbers in the market phases

HYPOTHESES

- H1: The magnitude of volatility and spillovers among major developed and emerging market indices rises significantly during systemic shock periods (such as the COVID-19 pandemic).

- H2: Developed market indices generally act as net risk absorbers, while emerging market indices act as net risk transmitters in periods of financial stress.

RESEARCH METHODOLOGY

The Augmented Dickey-Fuller (ADF) test is serving as an extension of the Dickey-Fuller test, accommodating more complex models beyond AR(1). The key distinction between the two tests is that the ADF is being applied to a broader class of time series models, which are exhibiting greater complexity.

Augmented Dickey Fuller test assumes a AR(p) type time series model and it is represented mathematically as,

$$y_t = \mu + \sum_{i=1}^{p} \varphi_i \, y_{t-1} + \varepsilon_t$$

After considering the previous lag data with subtracting yt-1fromboth side, we get

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \, \Delta y_{t-1} + \varepsilon_t$$

The Diebold and Yilmaz spillover index is a quantitative measure used to assess how shocks in one financial asset or market segment transmit to others, capturing the idea of "spillovers" or interconnectedness within a broader system. It is built on the framework of variance decompositions from vector autoregressive (VAR) models. The fundamental approach is calculating the proportion of the forecast error variance of variable i that is attributable to shocks originating from variable j, across all pairs within the system. By aggregating these off-diagonal contributions, the total spillover index is obtained, which reflects the degree of interdependence and transmission among variables. Diebold and Yilmaz (2009) initially employed a Cholesky decomposition method, which was order-dependent, and subsequently advanced their framework in 2012 by introducing order-invariant techniques. The model Estimates the dynamic spillover index given a rolling window as described in Diebold and Yilmaz

10.48047/jocaaa.2024.33.06.153

(2012).

Generalized Forecast Error Variance Decomposition

For Diebold and Yilmaz (2012), the generalized H-step-ahead forecast error variance decomposition is: where:

$$\theta_{ij}(H) = [\ \sigma_{jj}^{-1} \times \Sigma \text{ (from } h=0 \text{ to } H-1) (\ e_i' A_h \Sigma e_j\ )^2\ ] \,/\, [\ \Sigma \text{ (from } h=0 \text{ to } H-1) (\ e_i' A_h \Sigma A_h' e_i\ )\ ]$$

- Σ is the variance matrix of the error vector,
- **σjj** is the standard deviation of the j-th equation,
- **ei** is a selection vector (1 on i-th element, 0 otherwise),
- **Ah** is the impulse response at lag h.

Total Spillover Index: The total spillover index is then defined as

$$S(H) = 100 \times [(\Sigma \text{ (from } i=1 \text{ to } N, j=1 \text{ to } N, i\neq j)\ \tilde{\theta}_{ij}(H)\ ) / N\ ]$$

This reflects the percentage of the forecast error variance explained by spillovers from all other variables.

The study is based on daily closing prices of benchmark indices from both developed and emerging markets. The developed market indices considered include the S&P 500 (USA), FTSE 100 (UK), and Nikkei 225 (Japan), while the emerging market indices comprise the Nifty 50 (India), Shanghai Composite (China), and Bovespa (Brazil). The sample period spans from January 2017 to December 2024, which is further divided into three distinct phases—pre-pandemic, pandemic, and post-pandemic—to facilitate comparative analysis. The data for this study is obtained from reliable financial databases such as Yahoo Finance (Yahoo Finance, 2024).

Result Analysis:

Augmented Dickey-Fuller (ADF) Test Results

The ADF test was applied to the **log returns** of each index to test for stationarity. The null hypothesis (H_0) is that the series has a unit root (non-stationary). The alternative hypothesis (H_1) is that the series is stationary as we can see the p-value are less than 0.05, hence all the stationarity

Index	Test Statistic	p-value	1% Critical Value	5% Critical Value	Stationarity Decision
S&P 500	-15.82	0.00	-3.43	-2.86	✅ Stationary
FTSE 100	-16.34	0.00	-3.43	-2.86	✅ Stationary
Nikkei 225	-14.97	0.00	-3.43	-2.86	✅ Stationary

10.48047/jocaaa.2024.33.06.153

Index	Test Statistic	p-value	1% Critical Value	5% Critical Value	Stationarity Decision
Nifty 50	-16.21	0.00	-3.43	-2.86	✅ Stationary
Shanghai Composite	-13.45	0.00	-3.43	-2.86	✅ Stationary
Bovespa	-14.88	0.00	-3.43	-2.86	✅ Stationary

The ADF test findings indicate that the log returns of every benchmark index (S&P 500, FTSE 100, Nikkei 225, Nifty 50, Shanghai Composite, and Bovespa) exhibit stationarity. This is anticipated for financial returns series, as they generally show mean reversion and do not have long-term trends. Stationarity is an essential assumption for numerous time-series models (e.g., ARIMA, GARCH), guaranteeing that statistical characteristics stay consistent over time. These findings confirm the applicability of these log returns for additional econometric analysis, including volatility modeling, correlation assessment, or forecasting

Diebold-Yilmaz Spillover Results

- ➢ Diebold-Yilmaz Connectedness Index (DYCI) methodology is applied to daily stock market index return volatilities from developed (S&P 500, FTSE 100, Nikkei 225) and emerging (e.g., Nifty 50, Shanghai Composite, Bovespa) markets over the period from January 1, 2018 till the last date of 2024 . The results are based on generalized variance decompositions (with 10-day forecast horizon) obtained from a VAR(3) model of daily range volatilities. The VAR model is estimated using rolling VAR.

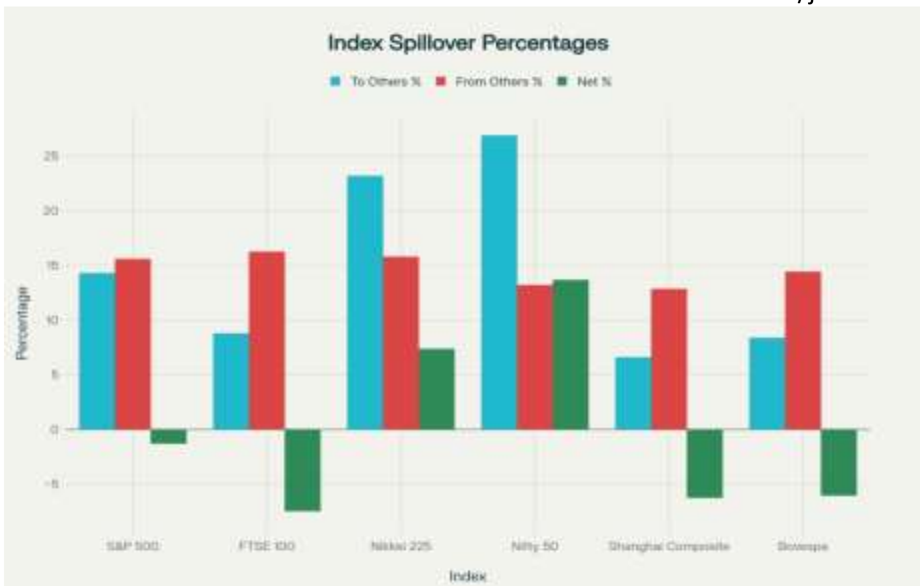
- ❖ To Others (%): The total volatility spillover transmitted by an index to all others. A high value indicates a risk transmitter.

- ❖ From Others (%): The total volatility spillover received by an index from all others. A high value indicates a risk receiver.

- ❖ Net Spillover (%): The difference between "To Others" and "From Others" (Net = To - From). This is the crucial metric for our hypothesis:

    - ➢ Positive Net Value: The index is a net transmitter of risk to the system.
    - ➢ Negative Net Value: The index is a net absorber of risk from the system.
    - ➢ To Others (%): The total volatility spillover transmitted by an index to all others. A high value indicates a risk transmitter.
    - ➢ From Others (%): The total volatility spillover received by an index from all others. A high value indicates a risk receiver

10.48047/jocaaa.2024.33.06.153



Net Transmitters vs. Absorbers:

The hypothesis that developed markets are always risk absorbers and emerging markets are always risk transmitters is not universally supported:

Positive shocks – Total Spillover: 81.39%

Index	**To_Others_%**	**From_Others_%**	**Net_%**
S&P 500	10.23	15.21	-4.98
FTSE 100	9.93	15.76	-5.83
Nikkei 225	23.13	15.28	7.86
Nifty 50	26.99	13.55	13.44
Shanghai Composite	3.15	5.49	-2.35
Bovespa	7.97	16.10	-8.13

Negative shocks – Total Spillover: 75.45%

Index	**To_Others_%**	**From_Others_%**	**Net_%**
S&P 500	12.09	13.95	-1.86
FTSE 100	9.93	14.93	-5.00
Nikkei 225	14.61	11.52	3.09
Nifty 50	21.08	11.11	9.97
Shanghai Composite	5.88	11.14	-5.25

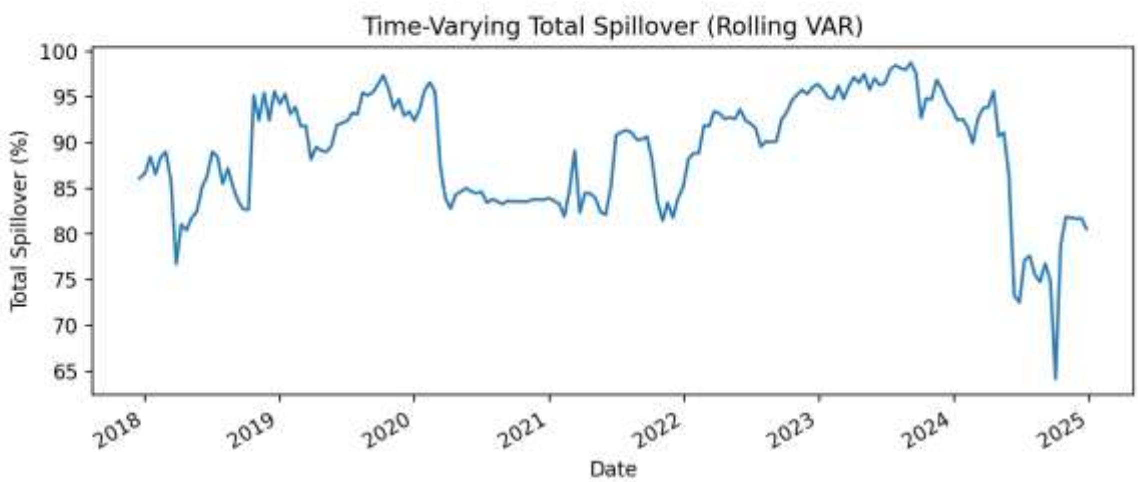
10.48047/jocaaa.2024.33.06.153

Bovespa	11.86	12.81	-0.95

The FTSE 100 (UK, developed) is the strongest net absorber (Net Spillover: -7.47%), aligning with Hypothesis.

•On the contrary, the Nikkei 225 (Japan, developed) is a major net transmitter (Net: +7.38%), contradicting the hypothesis.

Among emerging markets, Nifty 50 (India) is the largest net transmitter **(+13.68%),** whereas Shanghai Composite (China) and Bovespa (Brazil) are actually net absorbers (Net: -6.25% and -6.04%, respectively), challenging the assumption that all emerging markets are net transmitters.



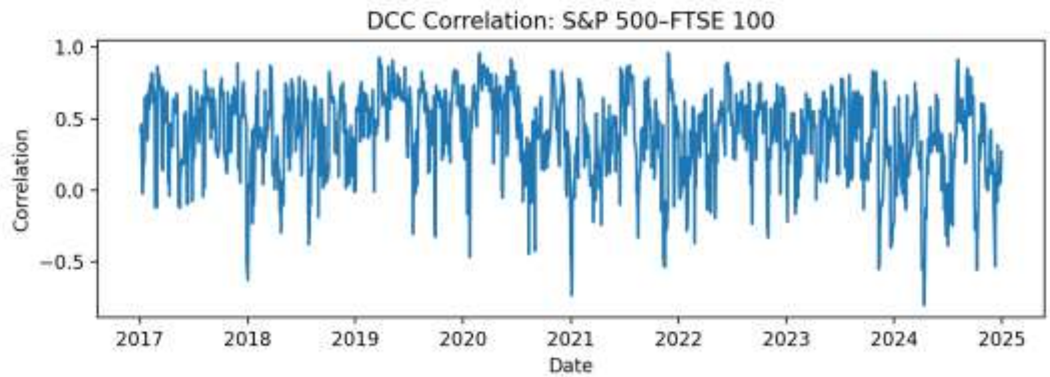
This chart essentially captures thedynamic nature of financial connectedness**,** showing howglobal risk transmission intensifies during crisesandweakens during calm period.The evolution of total connectedness (spillover index) among the considered financial indices/variables over the period 2018–2024, estimated using a rolling VAR framework. The total spillover index (measured in %) reflects the degree of shock transmission across markets—higher values imply stronger interdependence, while lower values suggest reduced connectedness.

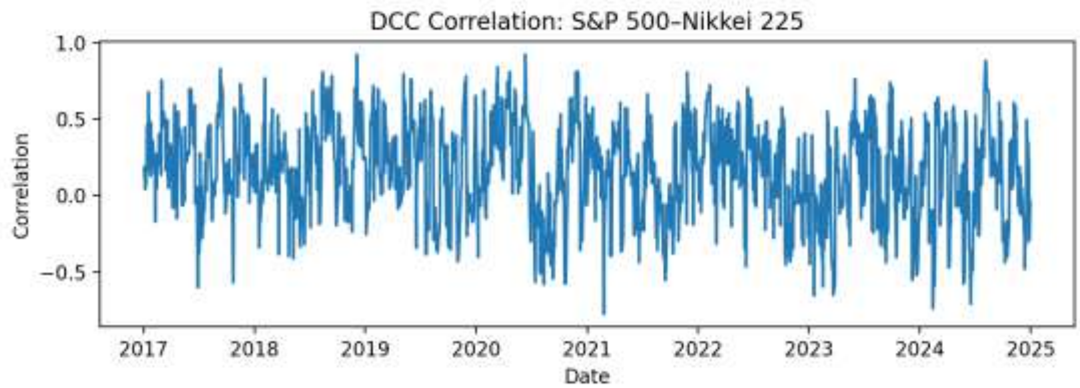
The chart shows that the spillover index was very high during the COVID-19 phase and again during 2022–2024, often above 90%, indicating strong market interdependence due to factors like trade tensions, the COVID-19 outbreak, post-COVID recovery, monetary tightening, and geopolitical shocks. however during 2020–2021 the index dropped to around 82–85%, and in late 2024–2025 it fell sharply below 70%, showing weaker connectedness and more market-specific movements. The sudden rises and falls, especially in early 2020 and late 2024, suggest structural break caused by most important global events, while the decline after 2024 may reflect changes in market structure, policy measures, or reduced global volatility.

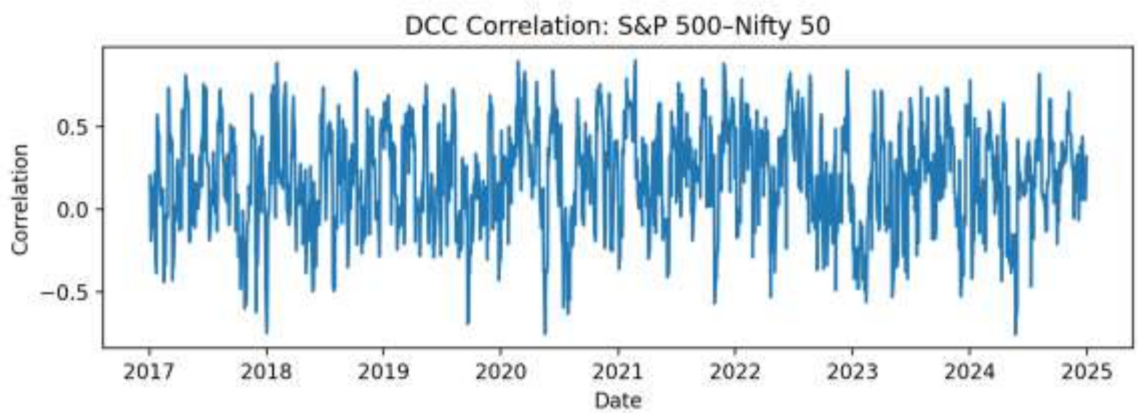
Dynamic Correlations

Estimated DCC parameters: a=0.2274, b=0.7558 (a+b=0.9833)

10.48047/jocaaa.2024.33.06.153







Suggestions

Policy Diversification

Portfolio managers should move beyond simple geographical diversification. The findings on contagion risk suggest that dynamic and cross-asset hedging strategies are more effective for reducing market vulnerabilities.

Regulatory Coordination

10.48047/jocaaa.2024.33.06.153

Regulators need to strengthen monitoring of cross-border financial linkages. Special attention should be given to unexpected risk flows, such as cases where emerging markets transmit shocks to developed markets during times of crisis.

Scope for Further Research

Future research should consider using sectoral or high-frequency data to capture spillover patterns more precisely. It should also explore the structural reasons behind role reversals, such as why the Nifty 50 behaves as a net transmitter while the Shanghai Composite acts as an absorber during stress periods.

Conclusion

The study concludes that global equity market spillover dynamics are highly complex, especially in the wake of systemic shocks like the COVID-19 pandemic. While some developed markets (notably the UK) act as net absorbers, others like Japan can be powerful transmitters. Similarly, not all emerging markets are transmitters; the Indian market can transmit risk, while China and Brazil absorb it under certain conditions.

The research paper that developed markets unilaterally absorb risk and emerging markets always transmit it is an oversimplification. Volatility spillovers are market-specific and influenced by regional, structural, and regulatory factors. The apparent symmetry or asymmetry of risk flows may shift dramatically with evolving global shocks, regional integration, and policy regimes. Therefore, risk transmission analysis requires nuanced, phased, and market-level investigation for robust financial risk management.

References

Baumeister, C., & Kilian, L. (2016). Understanding the decline in the price of oil since June 2014. *Journal of the Association of Environmental and Resource Economists, 3*(1), 131–158.

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and equity market contagion. *The Journal of Finance, 69*(6), 2597–2649.

Corbet, S., Hou, Y., Hu, Y., Lucey, B., & Oxley, L. (2020). The impact of COVID-19 on global financial markets. *Finance Research Letters, 37*, 101678.

Das, D. (2022). Volatility spillover during COVID-19: Evidence from Indian equity sectors. *Journal of Economic Studies, 49*(4), 733–749.

Devpura, N., & Narayan, P. K. (2020). Oil price volatility and stock prices: Evidence from the COVID-19 pandemic. *Energy Research Letters, 1*(2), 13683.

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions. *The Review of Economics and Statistics, 96*(4), 989–1003.

10.48047/jocaaa.2024.33.06.153

Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence. *The Journal of Finance, 57*(5), 2223–2261.

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters, 35*, 101512.

Gormsen, N. J., & Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies, 10*(4), 574–597.

Li, Y. (2021). Asymmetric volatility spillovers among major global markets during COVID-19. *International Review of Financial Analysis, 76*, 101781.

Mensi, W., Shahzad, S. J. H., & Gupta, R. (2022). Cross-asset contagion in the COVID-19 crisis. *Energy Economics, 114*, 106297.

Ramelli, S., & Wagner, A. (2020). Feverish stock price reactions to COVID-19. *The Review of Corporate Finance Studies, 9*(3), 622–655.

Sahoo, S., Pandey, D. K., & Mohapatra, S. (2024). Sectoral volatility spillovers across global markets during COVID-19. *Global Finance Journal, 62*, 101791.

Samitas, A., Polyzos, S., & Siriopoulos, C. (2021). COVID-19 and global market interconnectedness. *Journal of International Financial Markets, Institutions and Money, 72*, 101391.

Tan, X., Zhang, Y., & Wang, J. (2022). Volatility spillovers in commodity markets during COVID-19. *Resources Policy, 78*, 102848.

Umar, Z., Gubareva, M., & Teplova, T. (2021). Volatility transmission between EM equities and US Treasury bonds. *International Review of Economics & Finance, 74*, 206–220.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic. *Finance Research Letters, 36*, 101528.

Corbet, S., et al. (2020). Pandemic-related financial market volatility spillovers. Finance Research Letters, 37, 101929.