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Volatility Spillovers from The Vix to Global Equity Markets: Evidence from a Garch–Var Framework

SIVANI P S[1], DR P. A MANOJ KUMAR[2]
[1,2]School of Business and Management, CHRIST (Deemed to be University), Bangalore, India

Abstract- The financial markets have become more interconnected in the global economy, and financial volatility shocks are spreading more quickly between countries. In this paper, we analyze volatility spillovers from the CBOE Volatility Index (VIX) to six major equity markets (S&P 500, FTSE 100, DAX 40, Nikkei 225, Nifty 50, and Hang Seng Index) during the daily period from January 2015 to December 2024. To estimate the conditional volatilities, the two-stage GARCH–VAR approach is used: First, the conditional volatilities are estimated using GARCH(1,1) models and then analysed in a VAR framework with impulse response functions (IRFs), forecast-error variance decomposition (FEVD) and spillover methodology developed by Diebold and Yilmaz (2012) assisted by Granger causality tests. The empirical results verify the VIX's status as a structurally dominant net transmitter of volatility in the global economy, and the presence of directional and asymmetric spillovers to all markets sampled. Developed European markets, in particular the FTSE 100 and DAX 40, exhibit stronger and more persistent responses than emerging Asian markets. Regime-wise analysis shows that during the COVID-19 crisis period, total system connectedness significantly rises to 58.96%, and then decreases in the post-pandemic phase to 21.47%, highlighting timevariation and regime sensitivity of international volatility transmission. The findings are relevant for the portfolio rebalancing channel as the main propagation mechanism, and offer policy implications for portfolio diversification, risk management, and macroprudential policy design.

Keywords: VIX, Volatility Spillovers, GARCH–VAR Framework, Global Equity Markets, Financial Contagion, Risk Transmission, Diebold–Yilmaz Spillover Index, Regime Analysis

I. INTRODUCTION

Over the last 30 years, deepening cross-border investment flows, liberalisation of capital markets and the development of financial technology have revolutionised global finance. The once-segmented national equity markets have turned into a very connected network of markets, where financial shocks are transmitted quickly from one centre to the other. This integration would improve market efficiency and widen investors' choices, but would also increase each country's sensitivity to external shocks to a degree that is significant for both investors and risk managers and, importantly, for policy makers.

Volatility is a summary measure of uncertainty in asset prices, and is central to investment behavior, pricing of derivatives, and portfolio risk management. Significant volatility periods are generally marked by increased co-movement of stocks in equity markets (Engle and Bollerslev, 1986; Diebold and Yilmaz, 2012) and thus systematically reduce the benefits of international diversification. The study of the sources of volatility, its propagation and its persistence in markets is thus an important empirical issue in international finance.

The Chicago Board Options Exchange Volatility Index (VIX) plays a special role in this research program. The VIX is an index based on S&P 500 index option prices and is often called the world's "fear gauge," which is a forward-looking indicator of equity market volatility in the near future (Whaley, 2000). The United States is undoubtedly the leader in global financial markets, being the largest equity market, where institutional hedging activity is most prominent and has the world's most powerful reserve currency, and therefore a change in the VIX has also proven to have a significant impact on the risk sentiment and volatility throughout the world. High volatility of the VIX is commonly related to coordinated portfolio deleveraging, risk-off reallocation of capital and synchronized volatility increases in developed and emerging economies during periods of financial stress.

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While there is a large empirical literature on the spillovers of VIX (see, for example, Sarwar, 2012; Badshah, 2018; Balcilar et al., 2019), the majority of the studies have been undertaken using pre-pandemic data, have focused on specific crisis periods, or have not used the methods that enable systematic regime comparison. The period after 2015 is especially rich in empirical opportunities, ranging from a relatively stable pre-pandemic phase (2015–2019), to the acute phase of the COVID-19 pandemic (2020–2021), and finally a heterodox recovery, defined by inflationary pressures, monetary policy divergence and geopolitical tensions (2022–2024). There is limited evidence of the nature of volatility transmission in the various phases of the VIX.

This paper fills this void by examining the volatility spillovers between the VIX and six major equity indexes, namely S&P 500 (United States), FTSE 100 (United Kingdom), DAX 40 (Germany), Nikkei 225 (Japan), Nifty 50 (India) and Hang Seng Index (Hong Kong), from January 2015 to December 2024. The methodological approach combines the estimation of volatility using the GARCH(1,1) model with the spillover analysis framework of VAR, which includes IRF, FEVD and the Diebold–Yilmaz (2012) connectedness decomposition, along with Granger causality tests. The integrated design allows for simultaneous identification of the direction, size, and duration of volatility spillovers and the volatility regime dependence of the spillovers.

The study is made three main contributions. First of all, it offers recent post-2015 empirical evidence on how VIX volatility spreads globally in both developed and emerging equities in a common framework. Second, it reports relevant spillover differences between developed and developing economies, while accounting for this asymmetry in terms of structural differences in financial openness, capital mobility, and institutional investor participation. Third, it finds that the spillover dynamics of VIX are regime dependent, i.e. the spillovers are strongest during the COVID-19 crisis, moderate before the crisis, and strong after the crisis — with direct implications for time-varying risk management strategies.

The rest of the paper is structured as follows: A literature review is provided in Section 2. The data and econometric methodology is discussed in Section 3. The empirical results are presented and analyzed in Section 4. The results are analyzed in the light of previous studies in Section 5. The final part of Section 6 is a discussion of implications and future research.

II. LITERATURE REVIEW

2.1 Volatility and Global Financial Market Integration

Understand the concept of volatility and how this impacts on global financial market integration.

Theories of cross-market volatility transmission rest on theories of financial market integration, which suggest that the more mobile international capital becomes, the more volatile asset prices and risk premia are likely to be. The market integration and a transmission of shocks from major financial centres to markets within the country, which leads to greater cross-market correlations (especially in times of financial stress, when diversification benefits are reduced and systemic risk is increased) (Diebold and Yilmaz, 2009; Antonakakis et al., 2020). The literature is divided between unconditional co-movement, which is related to structural integration, and conditional contagion, which is related to synchronisation beyond normal levels during a crisis. Engle (1982) introduced the ARCH models and later on Engle and Bollerslev (1986) extended it to the GARCH framework which formed the basis of the econometric models used for modelling volatility and its propagation across markets.

2.2 VIX as a measure of global risk sentiment

In 2000, Whaley created the VIX, a forward-looking indicator of future volatility from S&P 500 index options. The VIX differs from realised volatility, which measures past volatility, as it captures market participants' expectations for the volatility of the future and reacts to new information regarding macro-financial risks. This forward-looking nature and the importance of U.S. equity markets in global asset pricing have made the VIX the de facto global risk sentiment gauge. A vast literature documents that increased VIX volatility expectations lead to greater

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co-movement across equity markets globally, suggesting that volatility expectations on US assets feed into the risk pricing of international assets (Sarwar 2012; Badshah 2018).

2.3 Empirical Evidence on VIX Spillovers to International Equity Markets

Among the earlier systematic evidence, Sarwar (2012) found that VIX shocks have a material impact on emerging market equity volatility, especially in times of increased uncertainty, and are highly asymmetric, with negative VIX shocks having a greater impact than positive ones. Badshah (2018) further explored these results in the VAR-DCC-GARCH framework to understand cross-market volatility linkages between the VIX and the VXEFA (developed-market volatility index) and VXEEM (emerging-market volatility index) and obtained similar findings, with a shock to the VIX accounting for roughly 57% and 64% of the forecast error variance of the VXEFA and VXEEM, respectively. Balcilar et al. (2019) report this dominance holds for both developed and emerging economies, and that the size of the spillovers grows during periods of systemic stress. Finally, Bouri et al. (2021) confirm that the link between uncertainty and international equity volatility strengthening during globalized crises, which is connected to the portfolio rebalancing and liquidity contagion channels.

2.4 Volatility Spillovers During Crisis Periods

There is an increased interest in the volatility spillovers being dynamic and regime dependent. Findings of Antonakakis et al. (2020), based on time-varying parameter VAR models, are consistent with theories of crisis-induced contagion, which hold that normally disjointed markets converge temporarily in times of crisis—for example, the global COVID-19 pandemic. An important aspect of the pandemic episode was its global simultaneity, which contrasted with the global financial crisis of 2008, which started in the US credit market and then radiated outwards. COVID-19 was an exogenous shock that impacted supply, demand, public health and fiscal positions across all major economies simultaneously. The simultaneous impact created feedback loops into the volatility expectations of the US, temporarily reducing the unidirectional dominance of the VIX and increasing overall system connectedness.

This chapter introduces two methodological approaches to volatility spillover analysis.In this chapter, two methodological approaches to volatility spillover analysis are introduced.

A number of related measures of volatility spillovers have emerged in the econometric literature. Although other methods have been proposed in recent years, GARCH-type models continue to be the most prevalent and popular methods of constructing conditional volatility series, in part due to their simplicity, empirical success, and their capacity to explain the volatility clustering and mean reversion properties of volatility (Engle, 1982; Engle and Bollerslev, 1986). The VAR framework offers a flexible structure based on data and without restrictive identification assumptions for analyzing interdependencies across different markets. The Diebold–Yilmaz (2012) spillover index is a new tool in the international volatility transmission literature constructed using FEVD of a VAR, which allows to explicitly decompose total and directional spillover as well as to identify net volatility transmitters and receivers among the markets. The Granger causality tests and IRFs complement each other in terms of causal relationships and shock impact persistence.

2.6 Research Gap

It is important to note that there are some gaps in the reviewed literature above. Very few studies use data that extend beyond the early phase of the COVID-19 pandemic or the recovery afterwards to be able to describe the dynamics of volatility transmission during that crisis and recovery. Furthermore, there are few studies that include a comparison of developed and emerging markets in a unified multivariate context and using recent data reflecting both the pandemic shock and the post-pandemic period. To fill those gaps, this study empirically examines the spillovers in VIX volatility across three different market regimes during the 2015–2024 time period and provides similar directional spillover evidence for six major equity markets.

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III. RESEARCH DESIGN AND METHODOLOGY

3.1 Data Description and Sample Construction

Data for the empirical analysis consists of daily closing prices of the CBOE Volatility Index (VIX) and six world equity indices for the period of January 1, 2015 to December 31, 2024. The indices are: S&P 500 (USA), FTSE 100 (UK), DAX 40 (Germany), Nikkei 225 (Japan), Nifty 50 (India), and the Hang Seng Index (Hong Kong). After alignment for non-synchronous national trading holidays, the final data set contains around 2500 daily observations, which cover a wide range of global equity market behaviour under different market conditions. Data for equity indexes are from Investing.com and are matched by the VIX, provided by the Federal Reserve Economic Data (FRED) data bank of the Federal Reserve Bank of St. Louis.

The sample period is strategically designed to cover three different market phases: a relatively stable pre-pandemic level (2015-2019); crisis phase of COVID-19 (2020-2021); and a post-COVID phase with different market conditions, including inflation, monetary policy divergence, and geopolitical tensions (2022-2024). The tripartite design allows for comparisons of spillover dynamics across regimes. All price series are first-differenced using a log transformation to make them stationery and scale-invariant, $r_t = \ln (P_t / P_{t-1}) \times 100$.

3.2 Hypotheses

Four directional hypotheses are tested in the study:

H1: The VIX is able to convey statistically significant volatility spillovers to the major equity markets in the world.

H3: The VIX is the net transmitter of volatility to global equity markets.

The VIX-induced volatility spillover effect varies across developed and emerging equity markets.

H4: There are distinct differences in volatility spillover patterns across calm, crisis and recovery market regimes.

3.3 GARCH (1,1) Volatility Estimation

A univariate GARCH (1,1) model is used to estimate time-varying conditional volatility for each of these return series. The mean equation is given by $r_t = \mu + \varepsilon_t$ while the conditional variance equation is $\sigma_t^2 = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$, with μ, α, β and ω being parameters such that $\alpha \geq 0$ represents the ARCH effect (sensitivity of current volatility to the past squared shocks) and $\beta \geq 0$ the GARCH effect (volatility persistence), with $\omega > 0$ being the long-run variance intercept. It is verified that $\alpha + \beta < 1$ for all series and is thus called the covariance stationarity condition (see Table 2). The estimates of the parameters are obtained by a quasi-maximum likelihood (QML) method, which is important for its robustness properties in the presence of fat-tailed innovations, as documented in Table 1 (Bollerslev and Wooldridge, 1992). As a result of the parsimony, theoretical motivation and its widely cited performance in capturing volatility clustering and mean reversion in international equity prices, the GARCH (1,1) specification is chosen rather than higher order specifications. The fitted conditional variance series $\hat{\sigma}_t^2$ for each market is then used as a proxy of market-specific time-varying volatility and is then used in the VAR framework. Before estimation, the goodness-of-fit of the GARCH (1,1) residuals is evaluated using the standardised and squared standardised residuals Ljung–Box tests to ensure there is no remaining serial correlation and ARCH effect.

All estimated conditional volatility series are checked for stationarity using the Augmented Dickey–Fuller (ADF) test with a confirmatory check using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test as this test has low power against near-unit-root alternatives. For all conditional variance series, the results of both tests confirm the stationarity of the series, thus no differencing is necessary before VAR estimation. The VAR model is given as $\sigma_t = c + \Sigma_{(i=1 \text{ to } p)} \Phi_i \sigma_{t-i} + u_t$, where the (7×1) vector σ_t denotes the conditional volatility series for VIX and the six equity indices, c is a vector of constants, the (7×7) coefficient matrices Φ_i describe lagged cross-market interactions, and the serially uncorrelated reduced-form innovations u_t follow a (7×1) distributed normal distribution with a (7×7) covariance matrix Σ_u. Both the Akaike Information Criterion (AIC) and a Schwarz Bayesian Criterion (SBC) are reported, with the former being considered the best criterion for determining the optimal lag order p.The best criterion for determining the optimal lag order p is the Akaike Information Criterion (AIC), which is also used as a robustness check, the Schwarz Bayesian Criterion (SBC). Model stability is checked by ensuring that none of the roots of the characteristic polynomial are in or on the unit circle, which means that there are not explosive dynamics of the estimated VAR. The generalised forecast error variance decomposition (GFEVD) of Pesaran and Shin (1998) is used as the basis for the spillover analysis, rather than that based on the Cholesky decomposition, because the generalised approach does not require careful ordering of variables in the VAR, a property which is particularly relevant in the present analysis where there is no natural causal ordering across international equity markets.

3.5 Spillover Analysis Framework

A set of three complementary instruments in a common framework based on GFEVD is used to quantify volatility spillovers. First, impulse response functions (IRFs) calculated with generalised impulse responses (Pesaran and Shin, 1998) provide an illustration of the conditional volatility of each equity market's response to a one standard deviation structural shock to VIX volatility, and indicate the level of magnitude, direction, and persistence in the transmission over a 10-year period, H. The confidence bands are built using 1,000 replications of the bootstrap simulation. Specifically, the generalised FEVD breaks down the h-step-ahead forecast error variance of each market's volatility into the volatility shocks that come from each system variable. In particular, let $d^g_{ij}(H)$ denote the contribution of variable j to the H-step FEVD of variable i, under a generalised decomposition: $d^g_{ij}(H) = \sigma_{jj}^{-1} \Sigma_{h=0}^{H-1}(e_i' A_h \Sigma_u e_j)^2 / \Sigma_{h=0}^{H-1}(e_i' A_h \Sigma_u A_h' e_i)$, where A_h are the moving-average coefficient matrices for the VAR, Σ_u is the error covariance matrix, σ_{jj} is the j-th diagonal element of Σ_u, and e_i is a selection vector. Note that the rows of the generalised FEVD do not add to 1, so the entries are normalised as $\tilde{d}^g_{ij}(H) = d^g_{ij}(H) / \Sigma_j d^g_{ij}(H)$. Third, the Diebold–Yilmaz (2012) spillover index operationalises the FEVD decomposition into four indexes of spillovers: the Total Spillover Index (TSI), $TSI(H) = (\Sigma_{i\neq j} \tilde{d}^g_{ij}(H) / \Sigma_{i,j} \tilde{d}^g_{ij}(H)) \times 100$, measures system-wide connectedness; the income indexes measure the connectedness of volatility from market i to all other markets, $(\tilde{d}^g_{ij}(H)) \times 100$, and from all other markets to market i, $(\tilde{d}^g_{ji}(H)) \times 100$; and the net indexes measure the overall direction of spillovers: to minus from, $(\tilde{d}^g_{ij}(H) - \tilde{d}^g_{ji}(H)) \times 100$. Complementary evidence for the predictive relationships between VIX volatility and international equity market volatility is provided by the Granger causality/block exogeneity Wald tests which are run in both directions to test for asymmetry of causation.

IV. EMPIRICAL RESULTS AND ANALYSIS

4.1 Descriptive Statistics and Stationarity Diagnostics

Table 1 presents descriptive statistics for the daily return series over the full 2015–2024 period. Mean returns are close to zero across all equity markets, consistent with the behaviour of high-frequency financial returns. The VIX exhibits considerably higher standard deviation than equity index returns, reflecting its role as a forward-looking uncertainty measure rather than an asset return. All series display statistically significant departures from normality: equity indices show predominantly negative skewness, indicating heavier left tails, while the VIX exhibits strong positive skewness consistent with sharp upward spikes during market stress. Excess kurtosis is present in all series, confirming fat-tailed distributions. Jarque–Bera statistics reject the null of normality at the 1% level for all variables. ADF statistics decisively reject unit roots at levels for all series, confirming stationarity and supporting direct GARCH and VAR estimation without prior differencing.

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Table 1: Descriptive Statistics and Stationarity Tests (2015–2024)

Index	Mean	Std Dev	Skewness	Kurtosis	Jarque–Bera	ADF Stat	Conclusion
VIX	−0.006	8.653	1.305	11.10	6382.44***	−49.38***	Stationary
S&P 500	0.051	1.195	−0.981	18.48	21461.64***	−22.60***	Stationary
FTSE 100	0.011	1.070	−0.815	15.21	13375.05***	−46.21***	Stationary
DAX 40	0.035	1.309	−0.513	13.39	9609.86***	−44.68***	Stationary
Nikkei 225	0.039	1.404	−0.558	12.90	8748.59***	−47.44***	Stationary
Nifty 50	0.049	1.104	−0.853	12.67	8487.62***	−45.76***	Stationary
Hang Seng	−0.008	1.458	−0.061	6.361	996.63***	−44.72***	Stationary

Note: ***$p < 0.001$. JB Test: Jarque–Bera normality test. ADF: Augmented Dickey–Fuller unit root test with constant and trend.

4.2 GARCH (1,1) Volatility Persistence

Table 2 presents GARCH (1,1) estimates for each return series. Both ARCH (α) and GARCH (β) coefficients are positive and statistically significant across all markets, confirming the presence of volatility clustering. The persistence parameter (α + β) remains below unity in all cases, satisfying the covariance stationarity condition. Equity markets exhibit very high persistence, with the DAX 40 (0.98), S&P 500 (0.97), and Nifty 50 (0.97) showing the slowest volatility mean reversion. The Hang Seng Index records the highest persistence (0.99), indicative of prolonged volatility following shocks, possibly reflecting heightened sensitivity to region-specific capital flow dynamics and structural vulnerabilities. By contrast, the VIX displays comparatively lower persistence (α + β = 0.70), consistent with its nature as a market-based expectation that reacts sharply to new information but mean-reverts more rapidly once uncertainty subsides.

Table 2: GARCH (1,1) Volatility Estimates

Index	ω (Intercept)	α (ARCH)	β (GARCH)	α + β
VIX	—	0.257	0.444	0.701
S&P 500	—	0.138	0.828	0.966
FTSE 100	—	0.137	0.792	0.929
DAX 40	—	0.080	0.899	0.979
Nikkei 225	—	0.129	0.827	0.956
Nifty 50	—	0.108	0.860	0.968
Hang Seng	—	0.075	0.910	0.985

Note: All α and β coefficients are statistically significant at the 1% level. ω values are near zero and not separately tabulated.

4.3 Hypothesis H1: Diebold–Yilmaz Spillover Decomposition

Table 3 presents the Diebold–Yilmaz spillover decomposition at a ten-period forecast horizon. The VIX transmits 54.69% of its volatility to other markets while receiving only 2.99% from them, yielding a strongly positive net spillover of +9.12 percentage points, confirming its role as a dominant net transmitter. All equity indices display negative net spillover positions, confirming that they are net receivers of global volatility. Among recipient markets, the FTSE 100 absorbs the largest normalised directional share (21.44%), followed by the S&P 500 (14.21%). The strong S&P 500 absorption is expected given the structural link between the VIX and its underlying index; elevated VIX levels directly reprice risk premia in US equities through hedging adjustments and risk-sensitive institutional trading. The DAX 40 displays a markedly large 'spillover from others' value (87.47%), indicating that the overwhelming majority of its conditional volatility forecast error is attributable to shocks originating outside Germany — a finding consistent with Germany's deep integration in global capital markets and its significant exposure to foreign institutional investors.

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Table 3: Diebold–Yilmaz Spillover Decomposition (H = 10 Forecast Periods)

Market	Own (%)	From Others (%)	To Others (%)	Normalised To (%)	Net Spillover
VIX	97.00	2.99	54.69	9.12	+9.12 (NET TRANSMITTER)
S&P 500	45.77	54.23	85.27	14.21	−40.02
FTSE 100	63.98	36.02	128.65	21.44	−14.58
DAX 40	12.53	87.47	33.01	5.50	−81.97
Nikkei 225	75.94	24.06	6.51	1.09	−22.98
Nifty 50	29.47	70.53	1.35	0.23	−70.31
Hang Seng	88.80	11.20	0.62	0.10	−11.09

Note: Own = percentage of forecast error variance explained by own shocks; From Others = spillover received; To Others = absolute spillover transmitted; Normalised To = share of total spillovers transmitted; Net = To minus From. H1 is confirmed.

4.4 Hypothesis H2: Direction of Volatility Transmission

Table 4 reports Granger causality test results alongside net FEVD-based spillover measures. VIX volatility Granger-causes volatility in all six equity markets at conventional significance levels ($p < 0.01$ in most cases). Reverse causality — from individual equity markets to the VIX — is statistically insignificant for four of the six markets, and only weakly significant for the FTSE 100 ($p = 0.0001$) and S&P 500 ($p = 0.0123$). The residual bidirectionality observed for FTSE 100 is economically interpretable: as a deeply integrated developed market with substantial dollar-denominated assets, FTSE 100 volatility may partially feed back into US investors' risk expectations. Nonetheless, the dominant directional pattern is unambiguously asymmetric: the VIX transmits to markets rather than receiving from them. This asymmetry is reinforced by the consistently negative net FEVD spillover positions of all equity markets, establishing the VIX as a centralised hub in the global volatility network rather than part of a symmetric bilateral feedback system. H2 is therefore supported.

Table 4: Granger Causality Tests and Directional Volatility Transmission

Market	χ^2 (VIX→Mkt)	p-value	χ^2 (Mkt→VIX)	p-value	Net FEVD (%)	Direction
S&P 500	2.248	0.325	8.797	0.0123*	−40.02	VIX → S&P 500
FTSE 100	14.086	0.0009***	18.501	0.0001***	−14.58	VIX → FTSE (partial feedback)
DAX 40	15.883	0.0004***	2.326	0.3125	−81.97	VIX → DAX
Nikkei 225	33.455	<0.001***	5.180	0.075	−22.98	VIX → Nikkei
Nifty 50	13.797	0.001***	1.203	0.5481	−70.31	VIX → Nifty
Hang Seng	13.430	0.0012***	0.751	0.6871	−11.09	VIX → HSI

Note: χ^2 statistics are from VAR Granger causality/block exogeneity Wald tests. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

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4.5 Impulse Response Analysis

Impulse response functions confirm that a one-standard-deviation shock to VIX volatility generates an immediate, positive volatility response across all sampled markets. The strongest contemporaneous response is observed in the S&P 500, consistent with the mechanical linkage between VIX and its underlying index. Among international markets, the Nikkei 225 and DAX 40 display relatively large initial responses, reflecting their deep integration into global trade and financial cycles and their pronounced sensitivity to shifts in global risk appetite. FTSE 100 also responds meaningfully, though its sectoral composition — with a high weight of multinational and commodity-intensive firms — partially moderates the sensitivity to short-term US volatility fluctuations. Emerging markets (Nifty 50 and Hang Seng) register comparatively muted initial responses, consistent with stronger domestic investor bases, partial market segmentation, and greater idiosyncratic local macroeconomic influences that dampen the immediacy of US-centric volatility transmission.

The shock responses persist for multiple periods before converging toward baseline levels, indicating that VIX shocks are not purely transitory. Developed markets exhibit slightly more extended adjustment paths than emerging markets, consistent with greater leverage, higher derivatives penetration, and faster cross-border capital flow responses. The persistence is consistent with the high GARCH parameters reported in Table 2 and with portfolio rebalancing dynamics that unfold over days to weeks rather than instantaneously.

4.6 Hypothesis H3: Developed vs. Emerging Market Spillover Differences

Table 5 disaggregates the VIX spillover contribution by market type. Developed markets receive an average normalised VIX spillover of 0.695%, approximately eight times the average received by emerging markets (0.087%). This substantial differential confirms statistically and economically meaningful asymmetry in exposure between the two market groups. Developed markets — characterised by higher capital mobility, greater foreign institutional participation, deeper derivatives markets, and closer integration with global asset allocation benchmarks — incorporate VIX-driven uncertainty more rapidly and completely into their volatility dynamics. Emerging markets, while not immune to global risk shocks, benefit from stronger domestic investor participation, partial capital flow management, and idiosyncratic macro-financial drivers that partially insulate them from direct transmission of US-based volatility surprises under normal conditions. Notably, however, this insulation weakens during systemic crises (as documented in Section 4.7), when cross-market correlations rise and the protective effect of structural heterogeneity diminishes. H3 is confirmed.

Table 5: VIX Spillover Contribution by Market Classification

Classification	Market	Spillover from VIX (%)	Group Average (%)
Developed	S&P 500	0.056	0.695
Developed	FTSE 100	2.469	
Developed	DAX 40	0.056	
Developed	Nikkei 225	0.200	
Emerging	Nifty 50	0.058	0.087
Emerging	Hang Seng	0.116	

Note: Normalised spillover contributions derived from FEVD-based Diebold–Yilmaz decomposition at H = 10. H3 is confirmed.

4.7 Hypothesis H4: Regime-Wise Variation in Volatility Spillovers

Table 6 reports directional VIX spillover measures and the Total Spillover Index (TSI) for each sub-period. During the pre-COVID phase, the VIX functioned as a strongly dominant net transmitter (net spillover = +16.11%), with minimal reverse feedback from international markets. Total system connectedness was moderate (TSI = 41.20%), reflecting a structured, US-centric volatility hierarchy in which changes in American risk expectations were systematically transmitted outward through portfolio rebalancing and dollar liquidity dynamics.

The structure shifts markedly during the COVID-19 crisis. Although the VIX remains a net transmitter, its dominance weakens considerably (net spillover falling to +5.50%), and total system connectedness rises sharply to 58.96%. This pattern reflects the globally synchronised nature of the pandemic shock: unlike previous US-centric episodes of financial stress, COVID-19 generated simultaneous disruptions across supply chains, public health systems, and fiscal positions in all major economies. Volatility therefore originated simultaneously from multiple jurisdictions, creating feedback loops back into US risk expectations and transforming the system from a hub-and-spoke into a more densely interconnected network structure.

In the post-pandemic phase, both VIX net dominance and total system connectedness decline markedly (net spillover = +2.38%; TSI = 21.47%). This fragmentation reflects divergent macroeconomic trajectories — energy price shocks concentrated in Europe, heterogeneous inflation dynamics and monetary policy responses, and region-specific geopolitical tensions — which caused equity market volatility to increasingly reflect local rather than global conditions. The declining centrality of the VIX in this phase does not imply its irrelevance but rather that post-pandemic volatility became more polycentric. H4 is confirmed.

Table 6: Regime-Wise VIX Spillover Dynamics and Total Spillover Index

Regime	Spillover to Others (%)	Spillover from Others (%)	Net VIX Spillover	Total Spillover Index (%)
Pre-COVID (2015–2019)	103.70	1.17	+16.11	41.20
COVID Crisis (2020–2021)	92.28	9.88	+5.50	58.96
Post-COVID (2022–2024)	44.41	5.03	+2.38	21.47

Note: TSI computed following Diebold and Yilmaz (2012) as the average 'Spillover from Others' across all system variables. H4 is confirmed.

V. DISCUSSION

All the empirical evidence is put together, gives a consistent and coherent description of the dynamics of the propagation of volatility from the US options market through the global equity system. A structurally asymmetric pattern is observed in all analytical instruments analyzed (variance decomposition, direction spillovers, Granger causality and impulse responses), with the VIX sending volatility to others and little volatility from others. This is not some statistical quirk, but rather the institutional structure of global finance. The VIX, the most widely tracked risk indicator globally, is a reflecting indicator for all institutional investors with diverse geographic and investment portfolios. The increase in VIX is likely to lead to portfolio rebalancing for risk-sensitive fund mandates, which includes reducing equity holdings, expanding credit spreads and buying safe-haven assets, and this action is likely to be synchronized across markets, via coordinated selling and futures and derivatives adjustments.

In line with this study, differences between developed and emerging markets are found to be heterogenous, which relates to the structural differences in financial openness and integration. They are more sensitive and lasting to VIX shocks because the developed markets (FTSE 100 and DAX 40) are deeply integrated in the same institutional investor networks that are referenced by the VIX in their risk governance and because the relatively high derivatives penetration in the developed markets allows for quick risk re-pricing. The Japanese experience (Nikkei 225) is a moderate case, as Japan is well-associated with the world through trade and finance, but the Bank of Japan's unconventional monetary policy and high institutional ownership reduce the speed of spillover transmission. Under normal circumstances, the relatively muted reactions of Nifty 50 and Hang Seng indices seem to be the result of a mix of capital account management, and larger domestic investor bases and idiosyncratic macro-financial considerations — although the rise in relationships in the COVID crisis shows that this insulation is conditional and not complete.

The findings support the methodological debate on the topic of international finance. The dramatic increase in the TSI to 58.96% during COVID-19 underlines the fact that the synchronisation during crisis is actually stronger than the synchronisation at normal integration levels and is therefore triggering a qualitative change in the topology of the global volatility network. This result is consistent with financial contagion theory (Forbes and Rigobon, 2002), which sets the structural spillovers apart from excess co-movement that arises from investor panic and liquidity constraints. The risk of a portfolio tail risk is therefore systematically underestimated by practical risk models assuming constant correlation structures during systemic crises. The post-pandemic drop in TSI, even to the pre-COVID level of 21.47%, is a new finding that indicates that volatility transmission has become more diversified as macroeconomic conditions have spread apart between regions, highlighting the increasing importance of domestic volatility over the global risk index.

This study builds on and refines the evidence presented in previous research in a number of ways. In this study, Sarwar (2012) and Badshah (2018)'s results that before the post-pandemic era the VIX was dominant are also supported and the time varying intensity of this dominance is documented using data ending prior to the post-pandemic era. The regime analysis directly responds to the gap identified in the literature by Antonakakis et al. (2020) and Bouri et al. (2021) related to the need for post-crisis evidence; moreover, the constant multivariate approach allows for the direct comparison of the three phases in a way that would not be possible with case-study or single-period analysis.

VI. PRACTICAL IMPLICATIONS

6.1 Portfolio Management

As the VIX was identified as a structurally dominant net transmitter of global volatility, it is clear the implications for international portfolio construction are direct. The underestimation of systemic risk under high spillover conditions is systematic in the case of static diversification assumptions, treating the cross-market correlations as constant. Investors should focus on the VIX and the direction of the spillover as forward-looking signals of potential diversification erosion, and consider adopting allocation frameworks sensitive to regimes that shift the weight of equity holdings, hedge ratios and cross market weights as the intensity of spillovers evolve. In high-connectedness periods, a diversification benefit can be achieved by raising the allocation to defensive assets, volatility sell-off stocks or low-correlation stocks.

6.2 Risk Management

The evidence of VIX-related volatility persistence, captured in impulse responses, suggests that short-term stress tests, that generally assume that the stress will quickly dissipate, will underestimate the total loss of the portfolio after a major stress event. Scenarios and VaR models should reflect extended adjustment horizons and multi-period volatility persistence in a risk management framework. The regime-conditional amplification of spillovers also indicates that dynamic hedging overlays with constant adjustments based on the real-time monitoring of spillovers would outperform static hedging during crisis periods.

The regulatory and policy implications are addressed. Regulatory and policy implications are discussed.
Macro prudentially, the VIX has maintained its status as a net transmitter, so that VIX-based spillover measures can provide valuable early-warning signals of increasing world-wide systemic risk. Regulators

can incorporate monitoring of directional connectedness into macroprudential surveillance processes to signal moments of increased cross-market volatility synchronisation, allowing them to take proactive measures to adjust capital buffers, margin requirements, or liquidity provision. The revelation that the spread of COVID-19 has shifted from the hub-and-spoke model to a more mutually reinforcing pattern, highlights the need to respond to crises internationally in a coordinated way when they are occurring simultaneously.

VII. CONCLUSION

The present study aims to analyse volatility spillovers from the VIX to six key global equity markets from the 2015–2024 period by employing GARCH-VAR framework with the Diebold–Yilmaz (2012) spillover methodology, impulse response analysis and Granger causality tests. The empirical results reveal that the VIX is a structurally significant net transmitter of global volatility, and that there exists directional and asymmetric volatility spillovers to all markets sampled, while there is very little reverse spillovers. The volatility reactions to VIX shocks are stronger and more persistent in developed markets than in emerging markets, which suggests that these markets are more financially open and have more mobile capital and more institutional investors. A regime analysis is performed to find that the overall connectedness of the system increases significantly during the COVID-19 crisis and decreases during the post-pandemic recovery phase, which provides a confirmation of the regime-dependent and time-varying volatility transmission in the system. The channel identified as responsible for the portfolio rebalancing is the same as the one used to explain that coordinated equity reallocations across the globe follow risk repricing through VIX.

Some constraints of this analysis must be noted. Potential nonlinearities and sudden structural changes in volatility transmission may not be fully captured by the linear VAR framework, and future studies can use threshold VAR or regime switching VAR models to have a more flexible regime definition to identify regime boundaries endogenously. Although commonly used and empirically sound, the univariate GARCH(1,1) model does not directly model the cross-market covariance dynamics and may benefit from multivariate GARCH models, e.g. DCC-GARCH or BEKK-GARCH. The study is limited to equity market volatility and excludes other channels of risk transmission such as bonds, commodities and foreign exchange. Lastly, the regime classification could be enhanced by a statistical estimation of the VIX threshold levels, instead of an exogenously defined threshold level.

Future research might continue this work into using nonlinear or time-varying parameter models to better capture asymmetric and threshold effects in spillover dynamics; adding other measures of global risk (EPU, MOVE index, credit spread) to the VIX to separate competing pathways of spills; and using more intraday high-frequency data to capture more rapid risk propagation mechanisms. These extensions are substantiated by the findings of this study – namely, the directionality of the relationship between VIX and volatility, the asymmetry, and the regime dependency – at an empirical level.

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