RESEARCH PAPER

Uncertainty-Driven Contagion in Global Equity Markets: Evidence from Volatility Spillovers During the GFC and COVID-19

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Received: 30th May, 2026; **Revised:** 11th June, 2026; **Accepted:** 15th June, 2026; **Available Online:** 18th June, 2026

ABSTRACT
Background
Dissemination of uncertainty in globally integrated financial markets has been one of the main issues of concern among academicians as well as policymakers. The paper investigates the question of how and whether global uncertainty (assessed by VIX index, the Oxford COVID-19 Stringency Index, and indicators of pandemic severity) magnifies the cross-border volatility transmission in equity markets.
Objective
The study considers 9 major stock indices in three separate regimes, namely the Global Financial Crisis (2006-2010), a period of relative stasis (2011–2018), and the COVID-19 pandemic (2019-2021).
Materials and Methods
Empirical strategy is implemented in two steps. In the former, conditional volatilities of GARCH(1,1) are estimated and rolling Diebold-Yilmaz spillover indices are also built, which will become the dependent variables in the second step. At this stage, the study proxy these time-varying spillovers on uncertainty measures, exchange rate stress and interest rate changes with Newey-West corrected standard errors.
Results
Four findings stand out. To begin with, VIX greatly increases volatility spillovers ($\beta = 0.315$, $t = 7.90$, $p < 0.001$), and the relationship is concave implying that the volatilities have a lower impact at extreme levels of uncertainty. Second, it is disproportionately transferred to emerging markets with a unit increase in VIX exerting an adverse impact on their net receiver position by 0.178% points ($t = -2.92$). Third, the COVID-19 Stringency Index is a strong and autonomous channel of contagion ($\beta = 0.846$, $t = 3.91$, $p < 0.001$), and during pandemic, it outperforms VIX as the most important explanatory factor ($\beta = 0.838$, $t = 4.14$). Fourth, volatility spillovers prove 1.28 times more responsive to VIX and 1.93 times more responsive to policy stringency than return spillovers, pointing to the second moment as the primary vehicle through which uncertainty crosses borders.
Keywords: Volatility Spillovers; Financial Contagion; VIX; COVID-19 Stringency Index; Diebold–Yilmaz Index; GARCH; Emerging Markets.
How to cite this article: Aggarwal A, Hugar GG. Uncertainty-Driven Contagion in Global Equity Markets: Evidence from Volatility Spillovers During the GFC and COVID-19. Int J Drug Deliv Technol. 2026;16(60s):1940-1950. DOI: 10.25258/ijddt.16.60s.175
Source of support: Nil.
Conflict of interest: None

1. Introduction

The last three decades have seen a tremendous interlinking of financial markets around the globe. The increase in cross-border capital motive investment driven by the liberalization of capital accounts, the high rate of rapid cross-border movement of shocks through electronic trading infrastructures have all made the financial environment in which a shock that is caused in one economy may be felt in another distant economy in hours [1]. This combination has already proven to have real advantages, namely, better capital set, even wider risk-sharing, and more profound liquidity. However, it is the same channels which are used to bring about effective capital flows in normal times which are the same channels which are used to spread shocks quickly under the conditions of stress. The dilemma of integration versus contagion is also a familiar concept since the Asian crisis of 1997-98, yet it is becoming all the more applicable with every new wave of instability [2].

There is significant evidence in the literature showing that cross-market spillovers increase in case of crisis. This intensification has been quantified through the use of the DieboldYilmaz framework [3, 4], and recently time-varying and frequency-domain decompositions [5, 6] have been used to measure it. But, the vast majority of these studies are descriptive: they inform us that crises raise spillovers but not the reason why. What causes a spillover index to increase from 50% and 65%? Is it increasing uncertainty, policy actions, currency pressures or some amalgamation? This creates a big gap with practical ramifications of risk management.

This study is inspired by specific empirical pattern. The previous study studied cross-market spillovers between 9 major equity indices. The increase in total return spillover was 52.6% of the benchmark period to 64.5% of the GFC and 63.0 % of the COVID-19. The volatility spillovers had a very different narrative as it increased by 33.2% to 65.3% (GFC) and 63.1% (COVID-19), which is almost four times more significant than the return channel. Such an asymmetry implies that the uncertainty transmission may end up being the major mechanism by which crisis-time contagion works due to the absence of a return co-movement. But what particular forces contribute to intensifying it our companion study did not inquire.

We organize our investigation around four research questions.

1. Does the VIX amplify volatility spillovers beyond crisis period fixed effects [7]?
2. Are emerging markets disproportionately vulnerable to externally generated uncertainty shocks [8]?
3. Did COVID-19 policy stringency create a distinct contagion channel independent of market-based uncertainty [9]?
4. Are uncertainty volatility spillovers more sensitive than uncertainty return spillovers?

The study employs a two-step model to respond to the above questions. The initial step is estimation of GARCH(1,1) conditional volatilities [10] and getting rolling DieboldYilmaz spillover indices that lead to a total of 2,899 daily observations that are the dependent variables. The second stage models them into VIX and the Oxford Stringency Index, the severity of COVID-19, the interest rates, and FX stress in NeweyWest (1987) standard errors. Interaction terms and sub-sample analysis allows to test the existence of changes in the effects between crisis and types of market.

This paper makes four contributions to the literature on financial contagion and uncertainty transmission.

- Driver-Based Spillover Analysis: Goes beyond the measurement of spillovers in a descriptive manner and explicitly models the rolling spillover indices as dependent variables, where financial connectedness is related to drivers of macroeconomic uncertainty.
- Policy–Contagion Link: Introduces the Oxford COVID-19 Stringency Index to establish a direct empirical relationship between government interventions and cross-border financial spillovers.
- Volatility Dominance in Uncertainty Transmission: Shows that the volatility spillovers are more sensitive to uncertainty when compared to return spillovers, indicating the weakness of the return-based risk measures.
- Emerging Market Vulnerability: Gives evidence that emerging markets (e.g., BSE Sensex, SSE Composite, JSE) become a greater net receiver of the spillovers, as uncertainty (VIX) increases, and has implications on the portfolio decisions and policy choices.

The remainder proceeds as follows: Section 2 reviews the literature, Section 3 develops the conceptual framework, Section 4 describes the data, Section 5 details the methodology, Section 6 presents findings, Section 7 discusses implications, and Section 8 concludes.

2. Literature Review

2.1 Financial Contagion and Crisis Transmission

The authors in [2] clearly stated the difference between the contagion aur interdependence. Contagion means that the connection between the markets increases suddenly after the crisis that do not exist before. Interdependence means that the markets were connected previously as well, but during the crisis the previous interconnections that existed previously as well are more intense and noticeable. Subsequent researches have proved that the co-movement during the crisis is more that takes place normally, which means some extra transmission takes place during the crisis, which do not happen normally. During the GFC period, the authors of [11] stated that the contagion is driven mainly by exposure of banking sector and uncertainty in the market. The researchers in [12] stated in their study that shocks from US market reached the markets of Europe and Asia rapidly. During the COVID-19 period, [13] concluded that in the early weeks of pandemic the markets around the world gave such an incredible synchronized reactions which was never seen before. The researchers in [8] found that contagion was not only limited to financial firms but also affected non-financial firms as well. All types of companies were affected during the pandemic. The difference between the two crisis periods is that contagion during the GFC period was driven by financial sector such as bank balance sheets, counterparty risks and loan defaults etc., whereas in COVID-19 period it was driven through real economy for example, lockdown forced business to shut down, supply chains were broken, and the most important was when lockdown was imposed commonly everywhere, the markets were effected badly which was felt commonly.

2.2 The Diebold–Yilmaz Spillover Framework

Diebold-Yilmaz framework represents a generalized forecast error variance decomposition derived using VAR models, and has been standardized as a measure of cross-market spillovers [3]. The Pesaran and Shin (1998) [14] decomposition was taken up in the 2012 extension and results are independent of the order in which variables appear. The further developments comprise network topology [4], frequency decomposition [6], TVP-VAR strategies [5], and the global bank connectedness [15]. One constant drawback is that these applications are descriptive - they will measure spillovers but fail to model the explanation of changes in their strength. The above gap is filled by the current study since it considers the rolling spillover index a dependent variable.

2.3 Uncertainty, VIX, and Financial Markets

VIX can be considered the most popular proxy of aggregate uncertainty [7]. It relates to contagion by creating portfolio rebalancing exogenous to VaR limits, which imposes simultaneous deleveraging [16] and liquidity spirals [17]. The authors in [18] demonstrated that the uncertainty shock created by COVID-19 was the biggest in history, whereas [19] revealed that predicted U.S. volatility is caused by global cases. The authors in [20] have associated the uncertainty of COVID to the oil and equity markets, and the researchers in [21] have reported a rise in connectedness of assets. Despite this work, the VIX is almost always a control variable, not the primary explanatory variable for time-varying spillover intensity, a gap which current study takes into account.

2.4 COVID-19 Policy Responses

Daily lockdown intensity of more than 180 countries were reported by the Oxford Stringency Index [9]. The authors in [22] noted that lockdown announcements had a negative effect on market performance in the U.S., [23] revealed stringency had negative effects on returns in 67 countries, and [24] saw governments lowering volatility and returns. [25] found increased U.S. monetary spillovers in the course of COVID. The only thing lacking is the test of whether the Stringency Index gives a predictive power of cross-border spillover dynamics, a gap which the current study fills in.

3. Conceptual Framework

3.1 The Uncertainty–Contagion Nexus

The study single out three mutually supporting channels. The operation of the information channel is facilitated by VIX as a globally observed common signal, [7] when it goes up, its co-movement with investors is also revitalized. Rebalancing channel necessitates institutions that are constrained by VaR to debrief geographies [16], with emerging markets being liquidated first, as the peripheral assets. The liquidity channel passes through spreading and drying up order books through the ETFs and derivatives [17]. These mechanisms are complements: a VIX spike will induce belief revision - push to the risk extremes - drain the peripheral liquidity - further enhance uncertainty.

H1: *VIX positively predicts spillover indices with a concave nonlinear form.*

H2: *Emerging markets' net receiver positions deteriorate as VIX rises.*

3.2 Policy Stringency as Contagion Channel

The lockdowns associated with COVID-19 [9] influenced markets in two directions: by shortening the expectations of incomes in a direct way, and a simultaneous commonality that amplifies co-movement was created [22]. This channel can be separated out of VIX since it reflects certain action in policy and not diffuse sentiment. The impetus of stringency by developed markets must be more so since developed economies are the node of the financial centre.

H3: *Stringency predicts spillovers independently of VIX, driven by developed-market stringency.* **H4:** *Cross-country stringency dispersion independently amplifies spillovers.*

3.3 Return versus Volatility Asymmetry

Uncertainty clearly increases the conditional variance but is not definite in directional changes in returns [26]. Research based on the idea of return correlation might fail in indicating crisis-time interconnectedness [27]. This is confirmed by our baseline data which show that volatility spillovers are more likely to rise by more than ~90%-97% compared to returns which rise by more than ~20-23%.

H5: *Volatility spillovers are more sensitive to VIX and Stringency than return spillovers.*

4. Data and Variables

We use the daily log returns of the nine index funds, five developed which are S&P 500, FTSE 100, DAX, CAC 40 and Nikkei 225 and four emerging, the SSE Composite, BSE Sensex, Bovespa and JSE, distributed by Yahoo Finance. The sample includes three periods the GFC (June 2006-December 2010, 919 days), a benchmark period (January 2011-December 2018, 1,595 days), and the COVID-19 pandemic (January 2019-December 2021, 585 days) with a summative number of observations 3,099. The descriptive statistics is reported in Table 1.

Table 1: Descriptive Statistics of Daily Returns

Panel A: GFC (2006–2010)	**Mean**	**SD**	**Skew**	**Kurt**	**Min**	**Max**
S&P 500	−0.0000	0.0177	−0.540	10.1	−0.138	0.104
FTSE 100	0	0.0174	0.016	8.38	−0.105	0.111
DAX	0.0002	0.0183	−0.004	9.04	−0.118	0.135
CAC 40	−0.0003	0.0194	0.26	7.9	−0.115	0.133
Nikkei 225	−0.0005	0.0204	−0.354	9.62	−0.127	0.137
SSE Composite	0.0005	0.0236	−0.380	2.3	−0.128	0.09
BSE Sensex	0.0008	0.0227	0.082	6.07	−0.128	0.16
Bovespa	0.0007	0.0241	−0.006	10.29	−0.188	0.169
JSE	0.0013	0.0254	0.476	6.89	−0.128	0.173
Panel B: Benchmark (2011–2018)	**Mean**	**SD**	**Skew**	**Kurt**	**Min**	**Max**
S&P 500	0.0004	0.0102	−0.394	4.84	−0.069	0.055
FTSE 100	0.0001	0.0103	−0.232	2.88	−0.048	0.051
DAX	0.0003	0.0136	−0.315	3.03	−0.071	0.064
CAC 40	0.0001	0.0135	−0.374	3.76	−0.084	0.056
Nikkei 225	0.0004	0.0146	−0.525	4.97	−0.112	0.074
SSE Composite	−0.0001	0.0153	−0.620	6.21	−0.089	0.101
BSE Sensex	0.0004	0.0107	−0.297	2.74	−0.061	0.051
Bovespa	0.0001	0.0162	−0.020	2.51	−0.092	0.086
JSE	0.0005	0.0167	−0.182	1.98	−0.088	0.068
Panel C: COVID (2019–2021)	**Mean**	**SD**	**Skew**	**Kurt**	**Min**	**Max**
S&P 500	0.0011	0.0157	−1.338	17.54	−0.128	0.09
FTSE 100	0.0002	0.0139	−1.023	13.46	−0.115	0.087
DAX	0.0007	0.0158	−0.722	14.85	−0.131	0.104
CAC 40	0.0007	0.0157	−1.084	13.78	−0.131	0.081
Nikkei 225	0.0006	0.0141	0.097	4.32	−0.063	0.077
SSE Composite	0.0006	0.0126	−0.104	6.64	−0.080	0.076
BSE Sensex	0.0008	0.0152	−0.590	8.7	−0.085	0.086
Bovespa	0.0003	0.0213	−1.394	16.31	−0.160	0.13
JSE	−0.0007	0.0196	−0.262	3.79	−0.101	0.074

Three patterns stand out. To begin with, the standard deviations approximately increase between the benchmark and crisis times S&P 500 is increasing by 1.02% to 1.77% (GFC) and 1.57% (COVID). Second, most markets exhibit negative skewness in returns to the COVID, which indicates the inverted March 2020 crash. Third, the excess kurtosis is significantly higher in both crises, and COVID has the highest (S&P 500: 17.54; Bovespa: 16.31), which has heavier tails, than during the GFC. Each market-period combination is estimated by GARCH(1, 1) models [10] which are estimated using maximum likelihood under conditional normality. The parameters are reported in table 2.

Table 2: GARCH(1,1) Parameter Estimates

Market	**GFC**			**Benchmark**			**COVID**		
	α	β	α + β	α	β	α + β	α	β	α + β
S&P 500	0.08	0.88	0.96	0.08	0.88	0.96	0.08	0.88	0.96
FTSE 100	0.08	0.88	0.96	0.079	0.865	0.943	0.08	0.88	0.96
DAX	0.08	0.88	0.96	0.08	0.88	0.96	0.104	0.843	0.947

CAC 40	0.08	0.88	0.96	0	0.999	0.999	0.077	0.845	0.922
Nikkei 225	0.092	0.853	0.946	0.078	0.773	0.851	0.08	0.88	0.96
SSE Composite	0.083	0.872	0.956	0.08	0.88	0.96	0.08	0.88	0.96
BSE Sensex	0.08	0.88	0.96	0.08	0.88	0.96	0.08	0.88	0.96
Bovespa	0.089	0.854	0.943	0.295	0	0.295	0.08	0.88	0.96
JSE	0.08	0.88	0.96	0	0	0	0	0	0

Note: $\sigma^2(t) = \omega + \alpha\epsilon^2(t-1) + \beta\sigma^2(t-1)$, Estimated via MLE under conditional normality. α+β measures volatility persistence.

The constant (α+β) of the volatility persistence is, on average, exceeds 0.94 in the GFC and in the COVID which is congruent with the well-documented near-unit-root behaviour of financial volatility [26]. The benchmark period is more heterogeneous - the Bovespa and JSE are less persistent which is indicative of more relaxed market conditions in which volatility shocks are more apt to fade faster.

The other explanatory variables will be as follows. As a measure of uncertainty, the study uses the VIX Index (FRED series VIXCLS), period means of 27.25 (GFC), 16.23 (benchmark) and 21.58 (COVID). We build up ΔVIX, VIX², log(VIX) and a high-VIX dummy (>75th percentile). Oxford Stringency Index [9] gives the daily government response intensity of each of the nine countries on a 0-100 scale; the study creates global, developed, emerging, and dispersion measures. The worldwide average is 49.1 (maximum: 78.0), zero in pre-COVID times. The severity of COVID is represented by the log-transformed global smoothed with Our World daily cases and deaths (peak cases: ~6.3 million; peak deaths: ~14,800). These controls are the Federal Funds Rate first difference (FRED DFF) and an EM FX stress index (mean absolute depreciation of ZAR of BRL, CNY, INR, and ZAR versus USD). Every variables arealligned to trading day frequency through forward-fill, leaving 2,899 full-observations after rolling window calculation.

5. Methodology

The methodology consists of 2 stages. Stage 1 will make the dependent variables including time-varying spillover indices based on the Diebold-Yilmaz structure. Stage 2 reverses these on uncertainty proxies to determine the spillovers driving factors. The entire methodological framework is shown in figure 1 schematically.

5.1 Stage 1: Diebold–Yilmaz Spillover Framework

We estimate a VAR(p) model for the K=9 market system.

$$Y(t) = c + A_{1Y}(t-1) + \cdots + A_{pY}(t-p) + u(t)$$

Here, $\mathbf{Y}(t)$ represents a $K \times 1$ vector containing either stock returns or GARCH-based volatility measures. The matrices $A_1, \ldots, A_p$ are the corresponding $K \times K$ autoregressive coefficient matrices, while $\mathbf{u}(t)$ is the error term, assumed to follow a multivariate normal distribution, i.e., $\mathbf{u}(t) \sim N(\mathbf{0}, \Sigma_u)$. The optimal lag length p is determined using the Bayesian Information Criterion (BIC), and the selected lag order is $p = 1$ for all sample periods.

Based on the estimated VAR model, the H-step-ahead generalized forecast error variance decomposition (GFEVD) is then computed using the approach of Pesaran and Shin (1998). An important advantage of this method is that the results do not depend on the ordering of the variables in the VAR system. The decomposition is given by:

$$\widetilde{\theta_{ij}}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Phi_h \Sigma_u e_j\right)^2}{\sum_{h=0}^{H-1} \mathrm{b} e_i' \Phi_h \Sigma_u \Phi_h'^{e_i}}$$

where Φ_h is the moving average coefficient matrix at horizon h, σ_{jj} is the j-th diagonal element of Σ_u, and e_i is a selection vector of dimension $K \times 1$. Since the row sums in the generalized decomposition are not automatically equal to one, each value is normalized by its row sum. This step ensures that the spillover contributions from all sources add up to one for
each market.

Using the normalized GFEVD matrix, we compute four spillover measures following Diebold and Yilmaz [3].These measures provide a clear picture of the overall level of connectedness across markets and also show whether a market mainly sends or receives shocks.

$$TotalSpilloverIndex: S = \frac{1}{K} \sum_{i \neq j} \widetilde{\theta_{ij}} \times 100$$

$$DirectionalSpilloverFromOthers: S_{i\leftarrow \cdot} = \sum_{j\neq i} \widetilde{\theta_{ij}} \times 100$$

$$DirectionalSpilloverToOthers: S_{\cdot \leftarrow i} = \sum_{j\neq i} \widetilde{\theta_{ji}} \times 100$$

$$NetSpillover: S_i = S_{\cdot \leftarrow i} - S_{i\leftarrow \cdot}$$

Here, the total spillover index measures the average contribution of cross-market shocks to forecast error variance. The directional measures show how much a market receives from others and how much it transmits to others. The net spillover value then helps identify whether a given market is mainly a shock sender or a shock receiver.

For the empirical analysis, the forecast horizon is fixed at $H = 10$. All spillover measures are estimated separately for return series and GARCH-based volatility series. To track how spillovers change over time, the VAR and GFEVD are re-estimated using a 200-day rolling window with a 1-day step. This process generates 2,899 daily observations for each spillover measure over the full 2007-2021 period. These rolling spillover estimates are then used as the dependent variables in Stage 2.

5.2 Stage 2: Uncertainty–Spillover Regressions

To understand what drives changes in spillover intensity, we regress the rolling spillover index on a set of uncertainty indicators and control variables:

$$\begin{aligned} S(t) = \alpha + \beta_1 \mathrm{VIX}(t) + \beta_2 \Delta\mathrm{VIX}(t) \\ + \beta_3 \mathrm{Stringency}(t) \\ + \beta_4 \log(\mathrm{Cases})\,(t) \\ + \beta_5 \log(\mathrm{Deaths})\,(t) + \beta_6 \Delta\mathrm{Rate}(t) \\ + \beta_7 \mathrm{FXStress}(t) + \gamma_1 D^{\mathrm{GFC}} \\ + \gamma_2 D^{\mathrm{COVID}} + \varepsilon(t) \end{aligned}$$

Here, $S(t)$ denotes the rolling spillover index at date t. The variables D^{GFC} and D^{COVID} are dummy variables representing the Global Financial Crisis and COVID-19 periods. In addition, $\Delta\mathrm{Rate}(t)$ measures the change in the Federal Funds Rate, while $\mathrm{FXStress}(t)$ captures the level of stress in emerging-market currency markets. This regression is estimated separately for four outcomes: total return spillover, total volatility spillover, emerging-market net return spillover, and emerging-market net volatility spillover. Because rolling-window estimates tend to create strong serial dependence in the dependent series, usual OLS inference is not valid. To obtain reliable standard errors, we use the Newey--West HAC estimator, which is robust to both heteroskedasticity and autocorrelation. The lag length is determined using the rule

$$\left\lfloor 4\left(\frac{T}{100}\right)^{2/9} \right\rfloor = 8$$

So, the inference is based on 8 lags.

5.3 Stage 3: Model Extensions

To check whether the baseline results differ across crisis periods and whether the effects are nonlinear, we estimate several extended specifications.

VIX × Crisis interactions: We include the interaction terms VIX × D^{GFC} and VIX × D^{COVID} to see whether the impact of uncertainty on spillovers changes during the Global Financial Crisis and the COVID-19 period relative to normal times.

Nonlinear VIX: We include VIX^2 to test whether the effect of uncertainty becomes weaker at very high levels of VIX, which would suggest that markets are approaching a limit in interconnectedness.

Stringency decomposition: The study disaggregate the global stringency index into measures of stringency in the developed markets, emerging markets and cross country dispersion of stringency. This can establish whether one group of policies in response to spillovers is more significant and whether the varied strictness of policies within countries contributes to further contagion.

Stringency × VIX interaction: This specification tests whether policy stringency and market uncertainty strengthen each other in increasing spillovers.

COVID-only subsample: We narrow down to 2019-2021 (584 observations) to investigate how stringency turns into the primary source of spillovers in the pandemic. It also permits the inclusion of cases, deaths, and stringency without the problem of zero-inflation that will be encountered in the complete sample.

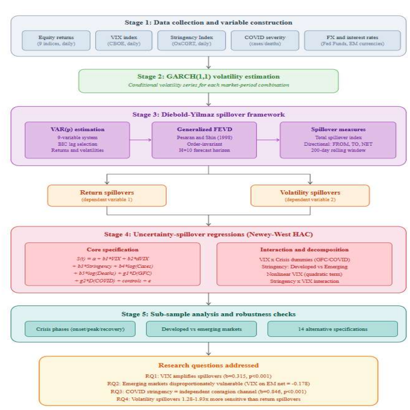

Figure 1: Methodological Framework — Two-Stage Uncertainty–Spillover Analysis

5.4 Stage 4: Sub-Sample Analysis

To capture differences across crisis stages, we divide the sample into six sub-periods using dummy variables. These correspond to the onset, peak, and recovery phases of the Global Financial Crisis and the COVID-19 crisis: GFC Onset (June 2006-August 2007), GFC Peak (September 2007-March 2009), GFC Recovery (April 2009-December 2010), COVID Onset (January 2020-February 2020), COVID Peak (March-June 2020), and COVID Recovery (July 2020-December 2021). These dummy variables are included in the regression as intercept shifters, allowing us to examine whether spillover behavior changes across the build-up, peak-stress, and recovery stages of each crisis.

5.5 Stage 5: Robustness Checks

We test the stability of the results across 14 model specifications, with 7 specifications for each spillover type. These include a VIX-only model, a model with VIX and crisis dummies, the full specification, a log (VIX) version, the full model including FX stress, a GFC-only subsample, and a COVID-only subsample. The main robustness check is whether the VIX coefficient remains positive and statistically significant in all cases, and whether its effect on volatility spillovers remains consistently larger than its effect on return spillovers.

6. Empirical Findings

6.1 Baseline Spillover Results

Table 1 shows a summary of Diebold-Yilmaz spillover decomposition done on the entire sample. The spillovers mentioned in returns increase to 52.6% (base) to 64.5% (Global Financial Crisis) to 63.0% (COVID-19 pandemic). On the other hand, volatility spillovers experience a significantly greater transition: of 33.2% to 65.6% (global financial crisis) and 63.1 (COVID-19 pandemic) and are more in line with the corresponding ~90-97%increase (which is much smaller compared to the ~20-23% of returns).

Table 1: *Total Spillover Index by Period (%)*

Type	Period	Total	FROM Dev	FROM EM	NET Dev
Return	**GFC**	64.54	75.79	50.47	+10.37
Return	**Benchmark**	52.57	66.12	35.64	+10.96
Return	**COVID**	62.96	73.72	49.50	+10.61
Volatility	**GFC**	65.55	77.30	50.87	+7.18
Volatility	**Benchmark**	33.17	41.24	23.08	+3.94
Volatility	**COVID**	63.14	76.53	46.39	+11.17

Note: Based on generalised variance decomposition from VAR(1) with H=10 forecast horizon.

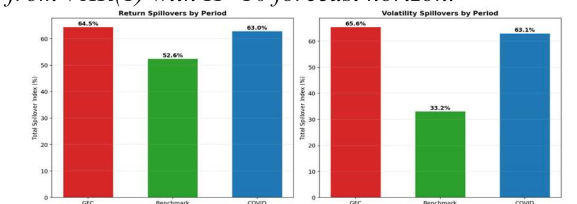

Figure 3: Total Spillover Index — Return vs Volatility by Period

The directional analysis shows that the European markets (CAC 40, FTSE 100, DAX) perform the role of a major net transmitter. The S&P 500 was a net receiver of volatility during the Global financial crisis (-4.4%) but shifted to become a net transmitter during the COVID-19 pandemic (+13.8%). It is worth noting that in the COVID-19 pandemic, the BSE Sensex was the greatest net receiver (−57.5%), indicating the extreme vulnerability of the Indian markets.

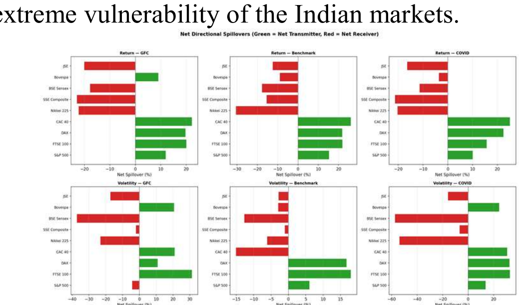

Figure 4: Net Directional Spillovers — Return and Volatility across Three Periods

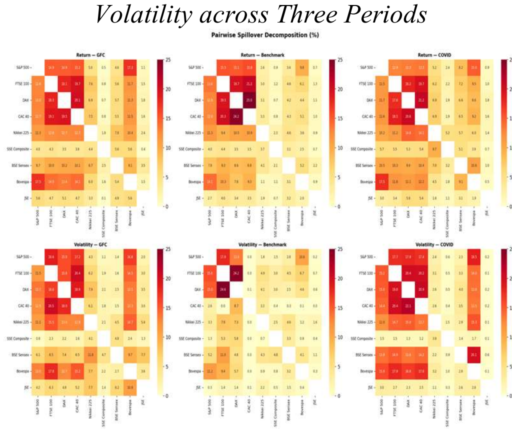

Figure 5: Pairwise Spillover Decomposition Heatmaps (%)

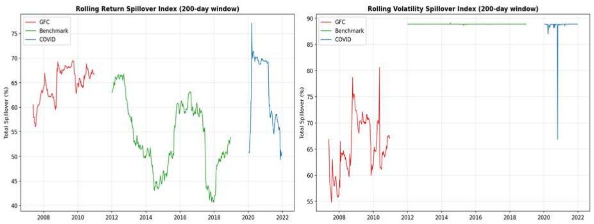

Figure 6: Rolling Spillover Indices (200-day window) by Period

6.2 VIX and Spillover Dynamics (RQ1)

The basic regression results are outlined in table 2. In the overall model, statistical significance of both return spillovers (β = 0.273, t = 7.33, p < 0.001) and volatility spillovers (β = 0.315, t = 7.90, p < 0.001) would be represented by indicators of Volatility Index (VIX). The VIX first differenced has a large and negative coefficient (−0.141 in returns, -0.231 in volatility) which appears to reflect a time lag in rolling windows of block busting changes in regimes. The nonlinear specification supports a concave association: VIX2 is considerably negative (β = −0.012, p < 0.001 for returns; β = −0.008, p < 0.001 for volatility), indicating the presence of decreasing marginal effects at VIX levels in the range of 50-60.

Table 2: *Core Regression Results — Full Model*

	Return	t-stat		Volatility	t-stat	
VIX	0.273	7.33	***	0.315	7.90	***
ΔVIX	−0.141	−3.40	***	−0.231	−3.96	***
Stringency	0.431	3.09	***	0.846	3.91	***
log(Cases)	0.832	0.73		0.309	0.13	
log(Deaths)	−2.956	−1.25		−5.957	−1.33	
D(GFC)	7.849	10.64	***	8.147	9.79	***
D(COVID)	−3.514	−6.22	***	3.711	2.60	***
EM FX Stress	−51.77	−1.14		111.28	2.43	**
ΔFed Funds	1.424	1.84	*	1.751	1.76	*
R²	**0.503**			**0.493**		
Obs	**2,898**			**2,898**		

*Note: Newey–West HAC standard errors (8 lags). *** p<0.01, ** p<0.05, * p<0.10.*

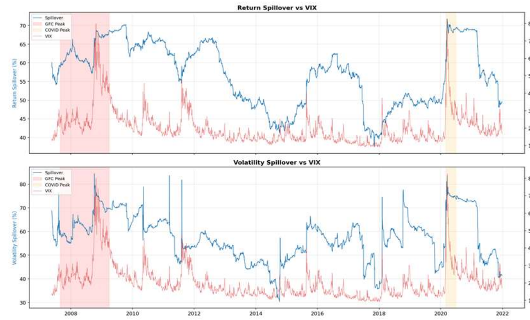

Figure 7: Rolling Spillover Index vs VIX (200-day window, 2006–2021)

The relations between VIX and crisis predictors explicate the fact that the global financial crisis (GFC) weakened the normal effect of the VIX when combined with the crisis dummy variable to (VIX×GFC = -0.387, t = -4.54 returns). The study achieves a high R^2 of 0.503 on returns and 0.493 on volatility in the comprehensive model and hence this lends support to the fact that our proxies of uncertainty explain about half of the time dependence in the spillover dynamics. Figure 7 is a visual representation of the high level of co-movement between VIX and the rolling spillover index, as both indicators follow strong peaks during the collapse of the Lehman Brothers and the March 2020 market crash triggered by the pandemic.

6.3 COVID-19 Stringency Effects (RQ3)

The Stringency Index is this paper's most novel finding. Each unit increase in global stringency raises return spillovers by 0.43 percentage points (t = 3.09, p = 0.002) and volatility spillovers by 0.85 percentage points (t = 3.91, p < 0.001). A one standard deviation increase (~25 points) translates to approximately 11 percentage points of additional return spillover and 21 percentage points of additional volatility spillover.

The stringency decomposition produces an imbalance. Developed-market stringency is highly significant (β = 0.329, p < 0.001 for returns; β = 0.578, p < 0.001 for volatility), while emerging-market stringency is insignificant in both cases. Cross-country stringency dispersion is also significant (β = 0.291, p = 0.032 for returns; β = 0.859, p < 0.001 for volatility), confirming that heterogeneous policy itself generates unreliability.

In the COVID-only subsample, stringency becomes dominant: β = 0.600 (t = 5.68) for returns and 0.838 (t = 4.14) for volatility, exceeding the VIX coefficient. The Stringency×VIX interaction is significant (β = 0.740, p = 0.001 for volatility), confirming that policy and market unreliability reinforce each other.

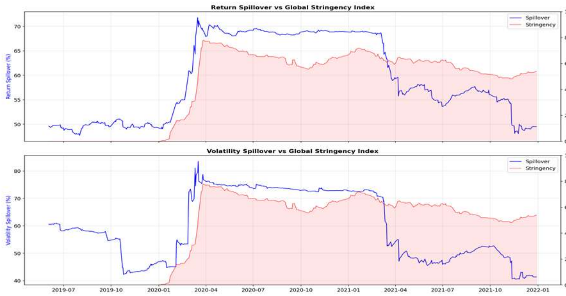

Figure 8: Rolling Spillover Index vs Global COVID-19 Stringency Index

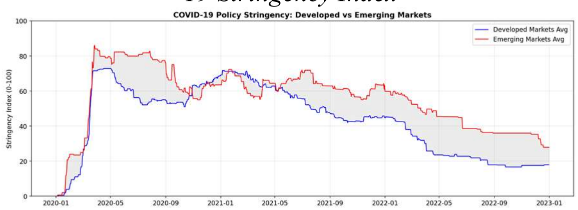

Figure 9: COVID-19 Policy Stringency — Developed vs Emerging Markets

6.4 Emerging Market Vulnerability (RQ2)

VIX is significantly negative for both return (β = −0.103, t = −4.84) and volatility net spillovers (β = −0.178, t = −2.92). The net position by emerging markets is deteriorated by 1.0% to 1.8% with every 10-point VIX rise. EM FX stress compounds this for volatility (β = −203.47, p = 0.003). EM stringency is important when the volatility net spillovers are (β = −0.655, t = −6.40) that is, domestic lockdowns in the emerging markets deteriorate their net receiver position but do not cause any outward contagion.

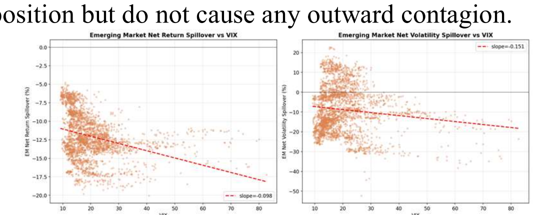

Figure 10: Emerging Market Net Spillover vs VIX

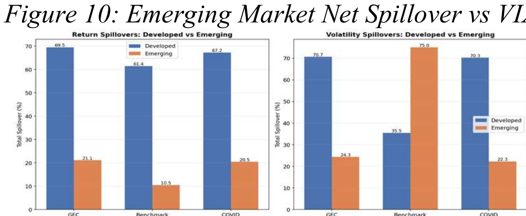

Figure 11: Spillover Comparison — Developed vs Emerging Market Subgroups

6.5 Return versus Volatility Sensitivity (RQ4)

Table 3 directly compares the sensitivity of the two spillover types using identical specifications.

Table 3: *Sensitivity Comparison — Return vs Volatility Spillovers*

	VIX β	Stringency β	log(Cases) β	R^2
Return	0.264***	0.340***	−0.803**	0.500
Volatility	0.338***	0.655***	−2.966***	0.485
Ratio (Vol/Ret)	**1.28×**	**1.93×**	**3.70×**	—

*Note: Identical specifications with VIX, Stringency, log(Cases), D(GFC), D(COVID). *** p<0.01, ** p<0.05.*

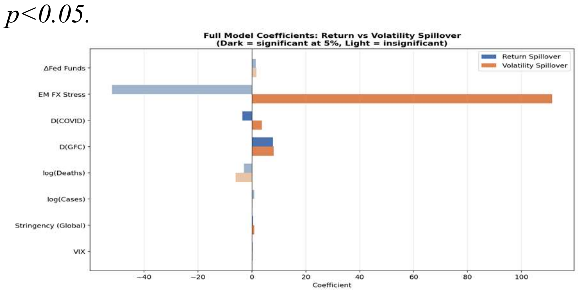

Figure 12: Full Model Coefficients — Return vs Volatility Spillover Comparison

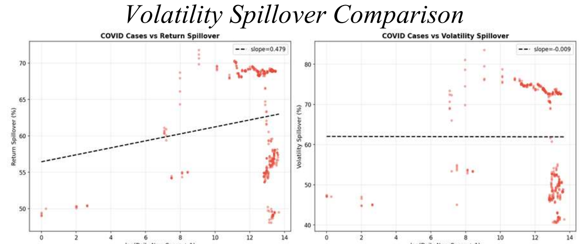

Figure 13: COVID-19 Cases vs Spillover Indices

6.6 Robustness Checks

We test 14 specifications across both dependent variables. The VIX coefficient is positive and significant at the 1% level in all 14 regressions, ranging from 0.153 (GFC subsample, returns) to 0.581 (VIX-only, volatility). R^2 ranges from 0.207 to 0.772. The COVID subsample yields the highest R^2 values (0.772 for returns, 0.502 for volatility). The volatility spillover VIX coefficient exceeds the return coefficient in every single specification, confirming the robustness of our RQ4 finding.

7. Discussion and Policy Implications

The fact that VIX has a steady significance in all specifications provides testament to the hypothesis that international uncertainty is a unique amplification mechanism, fixed effects of crisis are not limited to it. The concave association implies the most informative signals are in the 15-35 VIX region, which is used to calibrate early warning [16]. The most unique contribution of this paper is the importance of the Stringency Index lockdowns are a two-sided sword, the developed-market stringency gets global spillovers and the emerging-market stringency does not mirror the disproportional role of advanced economies as financial centers [11]. Stringency dispersion introduces an additional dimension: evaluation of recovery was complicated by the cross-country inconsistency of policies. Stringency is the dominant driver of the COVID subsample compared to VIX, indicating that observable policy variables had much of the explanatory power that indicators based on the market generally have.

The results that volatility spillovers are 1.28-3.70 times more susceptible to uncertainty prove the fact that crisis-time contagion is carried out mostly at the second moment. Risk management paradigms that assume correlations between returns underestimate systematically the interconnectedness of crisis times, which is in line with the models of the ambiguity aversion [7].

This is followed by four policy recommendations. First, real time volatility spillover indices which give alert signals earlier than the return correlations should be included in the macroprudential surveillance. Second, new-market regulators ought to design VIX-sensitive structures that have a set of intervention triggers that are triggered automatically as each 10-point rise in VIX deteriorates EM positions by 1.0%-1.8%. Third, international coordination needs to be sensitive to the financial externalities of non-financial interventions - global spillovers are created by the developed-market lockdown, and the policy heterogeneity by itself produces a contagion. Fourth, portfolio managers need to understood that crisis-time exposure is 1.3-1.9 times lower than indicated by return-based measures of diversification. Among its limitations are rolling window smoothing which can underestimate the rate of regime change, VIX tracking mostly U.S. equity uncertainty, and the linear structure of the framework that neglects threshold effects. Further studies may use TVP-VAR models, regional uncertainty indices, and wavelet coherence analysis.

8. Conclusion

This paper has examined how global uncertainty has increased cross market volatility spillovers in two major systemic crises. Based on a two-stage model that integrates GARCH-based volatility, Diebold–Yilmaz spillover indices, and Newey–West regressions, the study provide the evidence of four research questions on the basis of data related to nine equity markets, 2006-2021. Four findings emerge. First, VIX has substantial return and volatility spillovers ($\beta = 0.315$, $p < 0.001$ for volatility), which is concave. Second, there is disproportionately high exposure of emerging markets: net receiver positions deteriorate by 0.178% per unit VIX increase, a result of currency depreciation. Third, the COVID-19 Stringency Index is very strong (it is an independent contagion channel with ($\beta = 0.846$, $p < 0.001$) and at the pandemic subsample it overtakes VIX. Fourth, the 1.28-1.93 times higher sensitivity of volatility spillovers in comparison to return spillovers validate the dominance of channel of second moment. The inclusion of non-financial interventions into the responses to future crises by governments should be recognized to create cross-border financial externalities and the frameworks of response should be internationalized. To investors, the prevalence of the volatility channel means that models of returns will only bias exposure during a crisis. To regulators, conditionally deteriorated positions in emerging-market settings require pre-emptive, rule-based intervention frameworks, tuned to global uncertainty indicators.

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