Global Volatility Spillovers and Financial Contagion: Evidence from Developed, Emerging, and Frontier Equity Markets during the SVB and Credit Suisse Crises

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Abstract

The 2023 volatility in the banking sector, with the failure of Silicon Valley Bank (SVB) and the near-collapse of Credit Suisse, serves as a unique event to study the potential transmission of volatility across varying heterogeneous market structures. Utilizing GARCH(1,1) volatility estimates, event-driven comparisons, and Diebold–Yilmaz variance decomposition, we analyse the transmission of volatility across 15 equity markets (developed, emerging, and frontier markets), and the MSCI World Index. From January 2021 to December 2023, we collected 756 daily observations for each market. In our analysis, we found a high level of volatility persistence ($\alpha + \beta = 1$) and high values of kurtosis during the study period which indicate the presence of clustering of extreme values. The banking sector disruptions resulted in asymmetric responses across the markets. In the advanced markets, we observed high volatility that reversed over a very short time period, whereas, in the less developed markets, we observed prolonged volatility adjustments. In our study, we found values for the Total Connectedness Index (TCI) that were consistently over 120%. Canada and the United Kingdom were the main producers of volatility, while Japan appeared to be the main consumer of volatility. In particular, some of the frontier markets appeared to show possible insulation or alternative risk dynamics and showed no signs of immediate contagion as evidenced by the reduced volatility observed during the event windows. These observations illustrate the regional dependence of volatility and the need for a macro-prudential framework that incorporates the development gaps associated with varying levels of shock absorption and the speed of transmission.

Keywords: volatility spillover, financial contagion, GARCH, Diebold–Yilmaz connectedness, SVB collapse, Credit Suisse crisis, global market integration

1. Introduction

In March 2023, global financial markets felt shocks from the failure of two Systemically Important Financial Institutions (SIFIs) within nine days of each other. On March 10, 2023, Silicon Valley Bank (SVB) collapsed, and by March 19, 2023, Credit Suisse was forced into an emergency acquisition. Events like these are rarely seen and very difficult to understand, especially when they occur in different regulatory environments, such as the U.S. and Switzerland. The rapid and global banking disruptions of March 2023 are an indicator of a new evolution in the global banking sector and the profound, geographically unrestricted spread of financial crises. Whereas previous generations of investors experienced disruptions that were relatively contained in geography, disruptions today are able to cross borders within a matter of hours due to today's interconnected trading systems, unified investment strategies, and rapid data-sharing systems (Al-Sari, 2025; Martins, 2025).

Most scholars have studied the phenomenon of financial contagion, which is the transmission of crises beyond applicable fundamental economic linkages, due to the 2008 global financial crisis and the 2020 pandemic-induced crisis. The 2023 banking turbulence is, however, still underexamined. The 2023 banking turbulence is different from the other two phenomena mentioned above. The other two involved broad, systemic crises: 2008 involved diffuse systemic stress, while 2020 was an exogenous health shock. The 2023 banking turbulence involved institution-specific failures in an otherwise stable regulatory environment. However, it still triggered a global response (Diebold et al., 2012; Hussain & Rehman, 2023). The literature has focused on developed markets and emerging markets. Oftentimes, there is a gap when it comes to the systematic analysis of frontier markets, despite the growing importance of these markets in cross-border capital flows (Samarakoon, 2011; Yarovaya et al., 2022). This study fills the gap in literature by analysing five developed, five emerging, and five frontier equity markets to analyse the extent to which structural features reduce the intensity and persistence of contagion (Bekaert & Harvey, 2002).

Our analytical approach combines (Kraus & Some, 2023) and (Prasad Yadav et al., 2025) GARCH volatility modelling with event-study methodologies and Diebold-Yilmaz spillover indices to examine the diffusions of shocks experienced by SVB and Credit Suisse by market categories. The integration of methodologies helps us to answer two specific questions. First, what extent of volatility variation across developed, emerging, and frontier markets was caused by these banking collapses? Second, in terms of the level of financial development, which markets were the key shock transmitters and receivers, and how were these roles defined? The study of fifteen markets and a global benchmark for three years, which encompasses a period of pre-crisis stability, an acute stress period, and a period of post-event normalisation, helps us to theorise asymmetric contagion and informs policymakers on the barriers of systemic risk and the diversification of risk in stress portfolios in a time when the domestic and international shocks are so closely intertwined.

2. Literature Review

2.1. Financial Contagion and Theoretical Foundations

Financial contagion occurs when a disturbance in one market causes a disturbance in another market that is out of proportion to what would be expected based on economic fundamentals and trade relations (Forbes & Rigobon, 2002). The basic models are explained by behavioural factors surrounding institutional herding, fire sales of correlated assets caused by liquidity issues, and domino effect selling caused by margin calls that are then magnified in interrelated markets (Kaminsky et al., 2003). The increasing global synchronisation of return and volatility distributions has been explained by advancements in trading technology and increased cross-border financial liberalisation and integration (Claessens & Forbes, 2001).

Importantly, while (Ali et al., 2024) posit that the regulatory reforms of the past decade, such as the post-2008 adjustments involving stress testing and capital requirements, remain insufficient towards the removal of contagion, the lack of such adjustments remains a problem. (Ali et al., 2024) suggest, for example, that during periods of heightened stress the channels of contagion remain more defined through channels of behavioural and technological contagion as opposed to the channels of technological contagion. The lack of adjustments towards behavioural contagion during stress periods remains problematic given the reforms of the past decade. The events during 2023 suggest that the banking system remains fragile, as the failure of both SVB and Credit Suisse highlights that even during jurisdictions that impose comprehensive post-crisis regulations, the continued presence of contagion brings to the forefront the failure of the current structures of regulations to hold the channels of rapid information dissemination and market algorithms, as these structures were designed to mitigate the rapid elements of the behavioural contagion through the adjustments of the banking system.

2.2. Volatility Spillover Measurement and Network Effects

The Diebold-Yilmaz methodology integrates GARCH family models and generalised variance decomposition to analyse directional volatility spillovers between markets (Diebold et al., 2012; Diebold & Yilmaz, 2011). It divides forecasts' variance error into domestic and international parts to identify shock transmitters and receivers. Studies show financial stress episodes make cross-market connectedness pronounced, especially when the correlation structure breaks, and diversification benefits are lost (Akhtaruzzaman et al., 2023; Antonakakis et al., 2020).

The literature identifies the United States, United Kingdom, and European financial centres as predominant volatility transmitters. Their extensive global connectedness, large networks of institutional investors, and benchmark status leading to global portfolio rebalancing, are the transmitters' criteria (Billah et al., 2025; Martins, 2023). On the other hand, emerging markets act as net volatility receivers; they are externally shock prone and contribute little to systemic volatility.

Such generalised observations of net receivers and transmitters come with caveats. While Japan is classified as a developed market, it often embodies net receiver characteristics due to its peculiar patterns of investor risk aversion. Larger emerging markets, particularly India and China, increasingly demonstrate transmitter characteristics, indicative of financial system maturation, coupled with foreign investor liberalisation. These instances illustrate that developmental classifications can mislead systemic market positions; analyses of specific market structures and levels of integration are warranted.

2.3. Empirical Evidence from Recent Banking Disruptions

The crises involving Silicon Valley Bank and Credit Suisse caused increased global volatility, especially in markets with a strong U.S. technology and European banking exposure (Aharon et al. 2023; Anyikwa and Nyika 2025). This impact was primarily through confidence and funding cost channels and not direct counterparty exposure, illustrating psychological and liquidity mechanisms as opposed to balance sheet interlinkages (Martins 2023). There was a clear asymmetric response in the markets. In developed markets, there was a significant spike in volatility that was quickly followed by a rapid period of calm. In emerging and frontier markets, as a result of poor liquidity and slow systems of information diffusion, there was a prolonged period of volatility that developed gradually (Gortsos 2023). Given this, the state of a market's development and the institutional quality of its systems appear to influence the extent to which they are able to absorb shocks.

2.4. Research Gaps and Contributions

Significant research gaps remain for 2023 banking disruptions, especially for unified methodology comparative studies between developed, emerging, and frontier markets (Bonga-Bonga & Ndiweni, 2025). Most research concentrates on developed markets, or singular emerging economies, which limits analysis on the development stage's contribution to contagion exposure and spillover effects across crisis phases (Shahzad Ijaz M & Tlemsani I, 2024). Few measures of bilateral connectedness also limit the scope of analysis. This research uses integrated GARCH, event studies, and rolling-window Diebold-Yilmaz methodology on fifteen markets. Network analysis (Lagoarde-Segot & Lucey, 2011) identifies the most significant transmission channels of shocks and demonstrates some of the gaps in the asymmetry of contagion and a research void beyond the developed and emerging markets.

2.5. Theoretical Transmission Mechanisms

There are three main channels through which volatility transmission occurs across markets. The first involves trade connectivity. Here, fundamental disruptions are disseminated across economies through import-export relationships, which in turn impact the equity values of involved trade partners (Forbes & Rigobon, 2002). However, these channels of trade do not fully explain the phenomenon of swift adjustments in financial markets, which occur in advance of any changes in the underlying real economy. The second concerns financial connectivity. Here, cross-border portfolios and banking result in direct exposure channels. Specifically, in the face of rational economic voids, market downturns lead to widespread selling across diversified portfolios (Kaminsky, 2003). Such banking crises also amplify these effects as counterparty risks that lead to frozen interbank markets. The last involves the behavioural/information cascade channels, which operate through investor sentiment and herding, whereby distress in one market (e.g. banking) can lead to portfolio fire sales across multiple markets (Claessens & Forbes, 2001). The effects of such portfolio fire sales can be further amplified through high frequency and algorithmic trading, which allow localised shocks to reverberate throughout the financial market system in mere minutes.

3. Research Methodology

This study focuses on the following two interconnected research questions: (1) How do the March 2023 failures of Silicon Valley Bank and Credit Suisse impact the collapses of developed, emerging and frontier equity markets in terms of creating differential volatility? (2) How were the international spillovers of volatility transmitted, and which markets, in the banking crises, were dominant transmitters and which were dominant recipients of the shocks? In order to answer these questions, it is necessary to employ various methods of analysis, as it concerns specific volatility dynamics of individual markets, as well as cross-market transmission frameworks.

3.1. Data and Sample Construction

Fifteen national equity indices' daily closing values were collected through the Bloomberg terminal for the time span of 1 January 2021 to 31 December 2023, yielding 756 observations of each equity market's closing value for each of the 756 trading days. The market selections were made with intent-based stratification for each of the three market developmental classes: five developed markets (S&P 500 of the United States; Nikkei 225 of Japan; Hang Seng of Hong Kong; S&P/TSX Composite of Canada; FTSE 100 of the United Kingdom); five emerging markets (Shanghai Composite of China; NIFTY 50 of India; Tadawul All Share of Saudi Arabia; TAIEX of Taiwan; DFMGI of United Arab Emirates); and five frontier markets (VN-Index of Vietnam; MASI of Morocco; DSEX of Bangladesh; MERVAL of Argentina; KSE 100 of Pakistan). The primary selection criteria were market capitalisation; thus, the most market cap dominant exchanges of each developmental tier were chosen to provide the most liquid and internationally dominant markets. The MSCI World Index represents an overall market sentiment indicator and dominant global equity benchmark the performance of which is used to compare market performance with the overall world equity performance.

3.2. Preliminary Statistical Analysis

The closing index value on day t is denoted as Pt. Therefore, the continuously compounded return is formulated as the natural log of the index values on consecutive trading days as $r_t = \ln(P_t / P_{t-1})$. The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) is applied to assess the unit root null hypothesis, which is used for checking the stationarity. The properties of the distribution (moments) are analysed, and the deviation from normality is examined using the Jarque-Bera test (Jarque & Bera, 1987). Returns and squared returns are examined for serial correlation using the Ljung-Box Q statistic, and for volatility clustering, the Engle's Autoregressive Conditional Heteroskedasticity (ARCH) Lagrange Multiplier (ARCH-LM) (Engle, 1982) test is utilised, and rejection indicates the presence of time-varying volatility suitable for GARCH processes.

3.3. GARCH Volatility Estimation

For extracting conditional volatility, the GARCH(1,1) specification (Bollerslev, 1986) was used, which models time/future varying conditional variance as: $\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2$, where σ_t^2 is the conditional variance at time t, ω is the positive constant, α is greater than or equal to 0 and captures the so-called ARCH effect (the impact from the recent shock), and β is greater than or equal to 0 and reflects the GARCH effect (the extent of volatility persistence). The mean reverting volatility condition is given by $\alpha + \beta < 1$. The closer the value is to 1, the greater the persistence as volatility shock decays slowly. The parameter estimates are derived via maximum likelihood estimation with Gaussian innovations and convergence was confirmed for all markets. The conditional standard deviations $\{\sigma_t\}$ represent the volatility series used for the later spillover analysis.

3.4. Event Study Protocol

The disruptions in banking were analysed using the event study methodology (Mackinlay, 1997), which was applied to two event dates: the SVB collapse on the 10th of March, 2023, and the Credit Suisse crisis on the 19th March, 2023. For the purposes of the event study, each of the events was given a symmetric window of baseline volatility and response window of ±30 trading days. This methodology was used since the 30-day window provides a good balance of capturing the full response of the volatility while limiting the impact of other unrelated events. This is in line with other studies that have focused on the banking crisis (Aharon et al., 2023). The SVB collapse occurred on 10 March, and the Credit Suisse crisis on 19 March, which gives us only nine calendar days (or six trading days) in between the two events. This creates overlaps between SVB events and the post-SVB events. This time proximity shows the real contagion dynamics where the SVB failure led to significant stress in the banking sector and ultimately an intervention in Credit Suisse. As a result, the Credit Suisse event window results incorporate additional volatility effects that are a result of the SVB shock, instead of fully independent responses. The use of a paired t-test to determine the difference in means of the conditional volatility in the given windows before and after the events is a good test for determining the validity of the changes in volatility before and after the banking event. The null hypothesis of each test was that there were no significant changes in conditional volatility, which was rejected, indicating there are substantial changes in the event of banking system collapses.

3.5. Diebold-Yilmaz Spillover Framework

The Diebold-Yilmaz Spillover Index assesses the degree to which markets influence each other through the transmission of volatility by separating the components of the error variance of forecasts into components of cross markets and own markets (Diebold and Yilmaz, 2012). The methodology uses N-variable vector autoregression (VAR) models employing Generalised Forecast Error Variance Decomposition (GFEVD), which is preferable to the Cholesky approach to obtain order-invariance (Pesaran and Shin, 1998).

The Total Connectedness Index (TCI) captures system interdependence and sums the off-diagonal elements. Spillovers To market i are the sums of the columns (excluding the diagonal), and spillovers From market i are the sums of the rows (excluding the diagonal). Net spillover is the difference between the spillovers sent and the spillovers received. This classification of markets into net transmitters (positive) and net receivers (negative) is applicable to the net spillover measure.

Dynamic connectedness analysis is based on 200-day rolling windows, which, combined with a five-day increment, allows the calculation of metrics that vary over time during the pre-, crisis, and post-crisis periods. The VAR lag length was determined by the Akaike Information Criterion, and in accordance with the literature, the forecast horizon was set to H=10 (Diebold and Yilmaz, 2011). In addition to the numerical analysis, network analysis was used, where the size of the nodes is proportional to the amount of net spillover, and the size of the edges represents the volume of bilateral spillover.

4. Results and Discussion

4.1. Descriptive Characteristics of Return Distributions

Table 1. Descriptive Statistics of Daily Returns

Market	N	mean	sd	min	max	skew	kurtosis
USA	756	0.0002	0.0133	-0.0530	0.0709	-0.1720	5.180
JAPAN	756	0.0002	0.0103	-0.0407	0.0386	-0.1106	4.109
HONG_KONG	756	-0.0005	0.0143	-0.0657	0.0869	0.5223	7.196
CANADA	756	0.0002	0.0074	-0.0315	0.0329	-0.2308	5.124
UK	756	0.0002	0.0078	-0.0396	0.0384	-0.5098	7.660
CHINA	756	-0.0002	0.0082	-0.0527	0.0342	-0.6116	7.332
INDIA	756	0.0004	0.0083	-0.0484	0.0488	-0.2758	7.168
SAUDI_ARABIA	756	0.0003	0.0076	-0.0463	0.0279	-0.7976	7.929
TAIWAN	756	0.0002	0.0094	-0.0445	0.0503	-0.2063	6.237
UAE	756	0.0007	0.0069	-0.0601	0.0389	-0.0649	13.18
VIETNAM	756	0.0000	0.0121	-0.0691	0.0470	-0.9698	7.452
MOROCCO	756	0.0001	0.0060	-0.0419	0.0495	-0.4415	15.01

BANGLADESH	756	0.0000	0.0069	-0.0423	0.0350	-0.0858	9.556
ARGENTINA	756	0.0031	0.0233	-0.1328	0.2057	0.3717	11.62
PAKISTAN	756	0.0004	0.0088	-0.0482	0.0574	-0.2179	8.207
MSCI_WORLD	756	0.0002	0.0087	-0.0373	0.0493	-0.0905	5.809

Table 1 provides descriptive statistics across 15 different markets. Daily returns are statistically very close to 0, which is in line with the weak-form efficient market hypothesis. Among all the markets, Argentina had the highest mean return of 0.0031 and highest volatility with a standard deviation of 0.0232. This can be attributed to macroeconomic volatility and frontier market risk premium. Developed markets are characterised by macroeconomic evenness with values of 0.0078 and 0.0074 for the UK and Canada, respectively. The majority of the markets are characterised by negative skewness which is an indication of crash risk. This means extreme negative returns are more probable than positive extremes. The markets have a very high value of kurtosis which is above 3. Among the countries, Morocco and the UAE had the highest values at 15.01 and 13.18, respectively. This justifies the use of GARCH models for volatility clustering analysis. The high percentage of non-zero returns (>70%) in all the markets, including the more illiquid frontier markets, supports the premise of reliable time-series analysis.

4.2. Stationarity Verification and ARCH Effects

Table 2. ADF and ARCH-LM Test Results

Market	ADF_Stat	ADF_pval	ARCH_LM_Stat	df	ARCH_pval
USA	-10.03	0.0100	82.70	10.00	0.0000
JAPAN	-10.60	0.0100	17.94	10.00	0.0560
HONG_KONG	-9.925	0.0100	84.52	10.00	0.0000
CANADA	-10.19	0.0100	70.30	10.00	0.0000
UK	-10.08	0.0100	63.76	10.00	0.0000
CHINA	-9.884	0.0100	53.43	10.00	0.0000
INDIA	-9.636	0.0100	62.83	10.00	0.0000
SAUDI_ARABIA	-9.079	0.0100	84.69	10.00	0.0000
TAIWAN	-8.837	0.0100	78.61	10.00	0.0000
UAE	-9.896	0.0100	63.45	10.00	0.0000
VIETNAM	-9.620	0.0100	67.31	10.00	0.0000
MOROCCO	-10.12	0.0100	46.76	10.00	0.0000
BANGLADESH	-9.898	0.0100	165.52	10.00	0.0000
ARGENTINA	-9.452	0.0100	88.11	10.00	0.0000
PAKISTAN	-8.656	0.0100	42.58	10.00	0.0000
MSCI_WORLD	-9.663	0.0100	60.44	10.00	0.0000

All fifteen markets and the MSCI World benchmark have at least one instance where the Augmented Dickey-Fuller statistics reject the unit root hypotheses at the 1% significance level as presented in Table 2, proving the stationarity of the return series and alleviating concerns of spurious regressions for the modelling. Arch-LM tests show evidence of conditional heteroskedasticity in all but the Japan market, which showed some $p = 0.056$ significance. The evidence of almost universal ARCH effects illustrates that the phenomenon of volatility clustering, where large price movements cluster temporally, exists in both mature and developing equity markets, which is consistent with the literature (Engle, 1982). The results of the tests provide evidence for the appropriateness of GARCH estimation in order to capture the time-varying volatility needed for spillover analysis.

4.3. GARCH Volatility Persistence Patterns

Table 3. GARCH(1,1) Estimates Across Markets

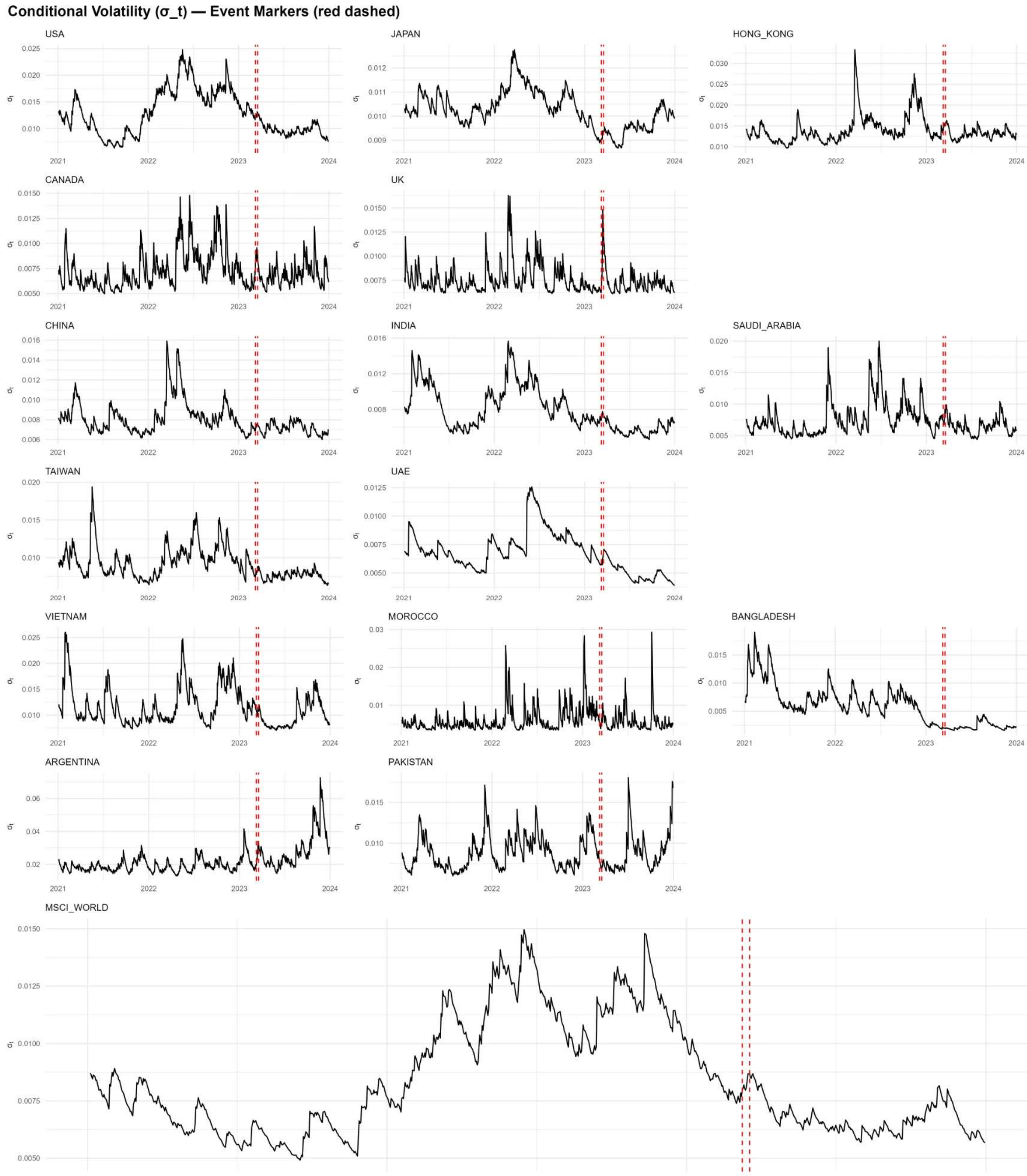
Market	Omega	Alpha	Beta	AlphaPlusBeta	Convergence
USA	0.0000	0.0507	0.9444	0.9950	Yes
JAPAN	0.0000	0.0127	0.9774	0.9901	Yes
HONG_KONG	0.0000	0.0566	0.9117	0.9683	Yes
CANADA	0.0000	0.1218	0.7934	0.9152	Yes
UK	0.0000	0.0831	0.7863	0.8694	Yes
CHINA	0.0000	0.0422	0.9335	0.9757	Yes
INDIA	0.0000	0.0483	0.9444	0.9927	Yes
SAUDI_ARABIA	0.0000	0.1188	0.8483	0.9671	Yes
TAIWAN	0.0000	0.0563	0.9156	0.9719	Yes
UAE	0.0000	0.0213	0.9761	0.9974	Yes
VIETNAM	0.0000	0.0767	0.8950	0.9717	Yes
MOROCCO	0.0000	0.3484	0.6290	0.9774	Yes
BANGLADESH	0.0000	0.0819	0.9144	0.9963	Yes
ARGENTINA	0.0000	0.0986	0.8764	0.9750	Yes
PAKISTAN	0.0000	0.0758	0.8989	0.9748	Yes
MSCI_WORLD	0.0000	0.0365	0.9566	0.9931	Yes

The estimates shown in Table 3 indicate that the GARCH(1,1) model reveals noticeable volatility consistency for each market, as the summed parameters ◎ + ◎ for each country get as close to 1 as possible. The most persistent volatility is in the United Arab Emirates (0.997), Bangladesh (0.996), and the United States (0.995). The volatility shocks in these markets are sticky/don't get to unconditional levels. This suggests that intervals of high uncertainty are likely to last for long periods of time before returning to normal. On the other hand, Canada (0.915) and especially the United Kingdom (0.869) show less persistence, which suggests that mean volatility for the markets is quite fast. This is likely due to Canada and England having more advanced markets where liquidity is deep and information flows efficiently. Therefore more volatility is observed.

The very high ARCH coefficient (α = 0.348) for Morocco is interesting. This indicates that there is more of the immediate effect of shocks in this frontier market. This is likely due to the case where there are lower levels of trading, and where the large trades that do take place can produce significant short-run volatility. The GARCH models for each country indicate that they all have the same level of specification, and the calculated conditional volatility series {σ_t} is to be used for analysing the cross-country transmission effects in the various episodes of the banking crises.

4.4. Conditional Volatility Dynamics

Figure 1. Conditional Volatility Series with Event Markers



The volatility series from the GARCH(1,1) models for the 15 markets and the MSCI World index (Figure 1) shows the first dashed line marking the SVB collapse (March 10, 2023) and the second, the Credit Suisse crisis (March 19, 2023). The illustrated volatility spikes seem to be the strongest for the USA, Japan and MSCI World, indicating a stronger spillover effect for these markets. The evidence from the Emerging and Frontier markets of India, Pakistan and Argentina shows the external shocks volatility in a more pronounced manner. In the USA, Japan and MSCI World, the collapse of SVB and the crisis of Credit Suisse seems to be pronounced. Developed markets like Canada and the UK seemed to have more contained volatility, with a faster return to pre-event levels. The prolonged volatility in the MSCI World index indicates that the crisis was global in nature.

4.5. Event Window Volatility Responses

Table 4. Event Window Test Results: Pre- and Post-Event Mean Volatility (All Markets, Both Events)

Market	Event	PreMean	PostMean	Diff	pval	Sig
ARGENTINA	SVB_Collapse	0.0207	0.0266	0.0059	0.0000	***
BANGLADESH	SVB_Collapse	0.0023	0.0019	-0.0004	0.0000	***
CANADA	SVB_Collapse	0.0059	0.0071	0.0013	0.0000	***
CHINA	SVB_Collapse	0.0068	0.0070	0.0001	0.2817	
HONG_KONG	SVB_Collapse	0.0129	0.0144	0.0015	0.0000	***
INDIA	SVB_Collapse	0.0067	0.0069	0.0003	0.0063	***
JAPAN	SVB_Collapse	0.0092	0.0093	0.0002	0.0002	***
MOROCCO	SVB_Collapse	0.0080	0.0058	-0.0022	0.0000	***
MSCI_WORLD	SVB_Collapse	0.0080	0.0080	0.0001	0.6535	
PAKISTAN	SVB_Collapse	0.0101	0.0073	-0.0028	0.0000	***
SAUDI_ARABIA	SVB_Collapse	0.0070	0.0078	0.0008	0.0033	***
TAIWAN	SVB_Collapse	0.0090	0.0078	-0.0012	0.0000	***
UAE	SVB_Collapse	0.0063	0.0065	0.0002	0.0907	*
UK	SVB_Collapse	0.0066	0.0090	0.0025	0.0000	***
USA	SVB_Collapse	0.0134	0.0118	-0.0016	0.0000	***
VIETNAM	SVB_Collapse	0.0117	0.0098	-0.0019	0.0000	***
ARGENTINA	CreditSuisse_Crisis	0.0208	0.0246	0.0039	0.0006	***
BANGLADESH	CreditSuisse_Crisis	0.0022	0.0019	-0.0003	0.0000	***
CANADA	CreditSuisse_Crisis	0.0066	0.0063	-0.0003	0.3293	
CHINA	CreditSuisse_Crisis	0.0071	0.0068	-0.0003	0.0048	***
HONG_KONG	CreditSuisse_Crisis	0.0135	0.0135	0.0001	0.8142	
INDIA	CreditSuisse_Crisis	0.0068	0.0066	-0.0002	0.1102	
JAPAN	CreditSuisse_Crisis	0.0091	0.0093	0.0002	0.0000	***
MOROCCO	CreditSuisse_Crisis	0.0069	0.0055	-0.0014	0.0045	***
MSCI_WORLD	CreditSuisse_Crisis	0.0079	0.0077	-0.0002	0.1305	
PAKISTAN	CreditSuisse_Crisis	0.0090	0.0072	-0.0019	0.0000	***
SAUDI_ARABIA	CreditSuisse_Crisis	0.0074	0.0075	0.0002	0.4794	
TAIWAN	CreditSuisse_Crisis	0.0084	0.0075	-0.0009	0.0000	***
UAE	CreditSuisse_Crisis	0.0061	0.0065	0.0004	0.0005	***
UK	CreditSuisse_Crisis	0.0074	0.0079	0.0006	0.2639	
USA	CreditSuisse_Crisis	0.0129	0.0111	-0.0018	0.0000	***
VIETNAM	CreditSuisse_Crisis	0.0114	0.0092	-0.0022	0.0000	***

Table 4 provides results from event window analyses illustrating the asymmetrical market behaviour during the two banking crises. During the collapse of Silicon Valley Bank (SVB), Argentina recorded the highest increase in volatility (+0.0059, $p < 0.001$), suggesting an increase in sensitivity to sovereign risk. This was followed by significant volatility increases in Hong Kong and the UK which correspond to their levels of international financial integration. In contrast, Morocco, Pakistan, Taiwan, and Vietnam exhibited lower volatility, suggesting an unwillingness to integrate financially, or a form of partial decoupling, possibly due to the imposition of capital controls. The reduction of volatility (-0.0016) in the United States was recorded after the Federal Reserve's actions. During the Credit Suisse crisis, Japan registered the largest increase in volatility (+0.0002) despite being a developed market, and this was due to exposure to European securities; however, the increases in volatility here are much smaller. Importantly, there was no increase in volatility of the MSCI World Index during either of the banking crises, which indicates that the failures were institutional and did not result in a systemic failure of the market.

Figure 2. Event Window Volatility Changes (Post - Pre)

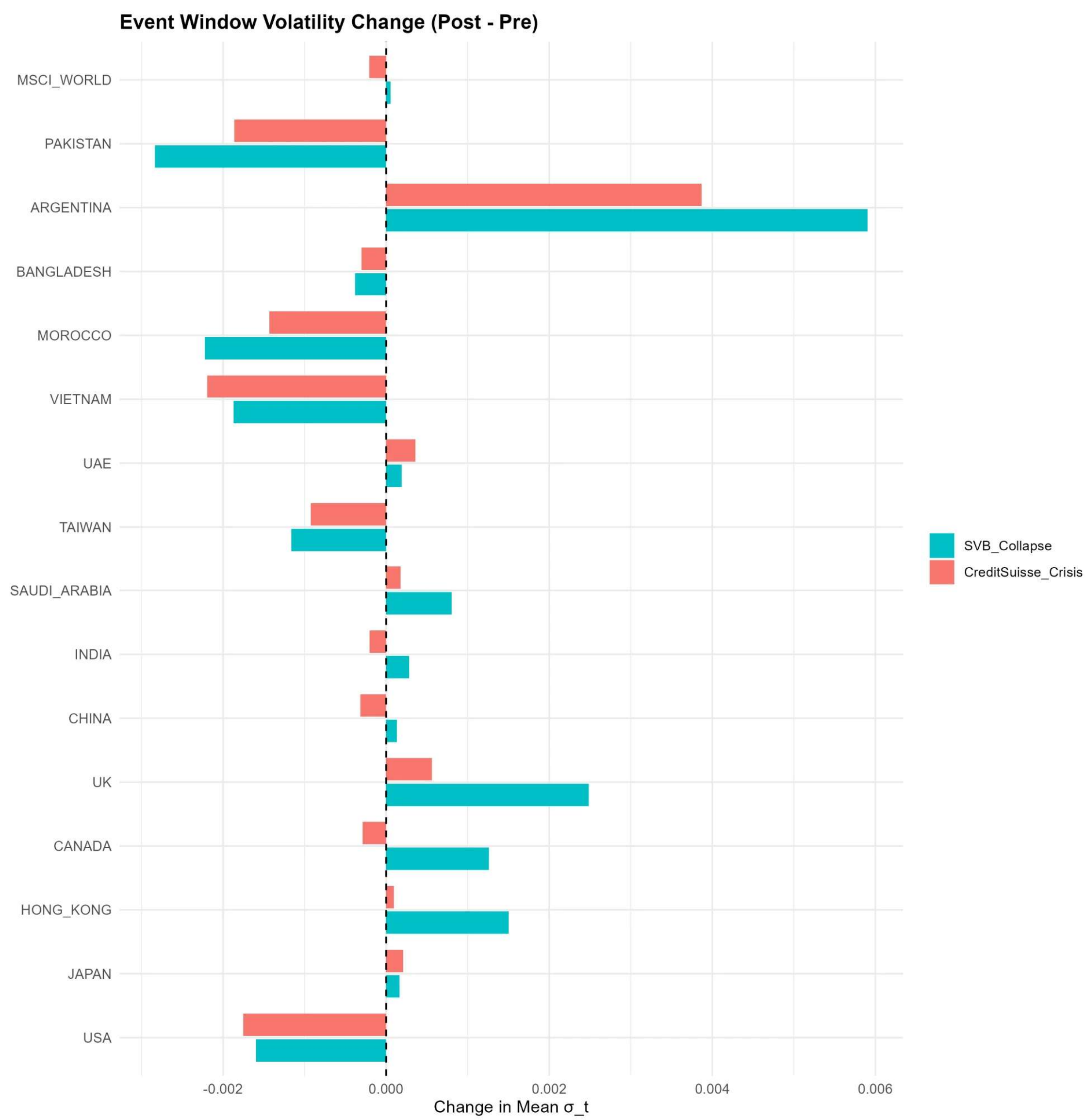


Figure 2 illustrates the differences between windows events in the mean conditional volatility. Argentina shows the highest increase in mean conditional volatility for both events. Some of the frontier markets show the highest mean conditional volatility reductions indicating possible partial insulation. The USA shows the lowest mean conditional volatility which could indicate the speed of policy reforms. The MSCI World index shows no mean conditional volatility which means that in contrast to the sharp regional mean conditional volatility, the global mean conditional volatility did not increase significantly.

4.6. Static Spillover Network Structure

Table 5a. Forecast Error Variance Decomposition (FEVD) Matrix

Market	USA	JAPAN	HONG_KONG	CANADA	UK	CHINA	INDIA	SAUDI_ARABIA	TAIWAN	UAE	VIETNAM	MOROCCO	BANGLADESH	ARGENTINA	PAKISTAN
USA	0.9333	0.0107	0.0293	0.4190	0.0750	0.0502	0.0536	0.0026	0.0137	0.0068	0.0533	0.0139	0.0005	0.0113	0.0071
JAPAN	0.1527	0.8491	0.0382	0.1582	0.2066	0.0114	0.1653	0.0156	0.1649	0.0144	0.0275	0.0204	0.0029	0.0137	0.0085
HONG_KONG	0.0852	0.0239	0.9105	0.0736	0.0715	0.3035	0.0244	0.0035	0.0375	0.0022	0.0384	0.0151	0.0030	0.0033	0.0015
CANADA	0.2920	0.0249	0.0130	0.9372	0.1323	0.0103	0.0585	0.0416	0.0285	0.0080	0.0679	0.0071	0.0021	0.0332	0.0063
UK	0.0610	0.0415	0.0124	0.1769	0.9296	0.0035	0.2000	0.0078	0.0301	0.0156	0.0206	0.0492	0.0037	0.0141	0.0040
CHINA	0.0207	0.0143	0.2456	0.0097	0.0319	0.9393	0.0329	0.0097	0.0269	0.0017	0.0322	0.0006	0.0103	0.0037	0.0037
INDIA	0.1013	0.0381	0.0064	0.1011	0.1355	0.0029	0.9290	0.0060	0.0250	0.0031	0.0209	0.0350	0.0113	0.0082	0.0069
SAUDI_ARABIA	0.0449	0.0065	0.0041	0.1060	0.0527	0.0007	0.0414	0.8272	0.0017	0.0881	0.0508	0.0136	0.0012	0.0025	0.0138
TAIWAN	0.0863	0.1172	0.0463	0.1078	0.1073	0.0161	0.0638	0.0008	0.9107	0.0361	0.0551	0.0177	0.0023	0.0052	0.0038
UAE	0.0382	0.0018	0.0056	0.0303	0.0588	0.0008	0.0113	0.0255	0.0066	0.8622	0.0677	0.0302	0.0222	0.0015	0.0073
VIETNAM	0.0248	0.0080	0.0055	0.1189	0.0298	0.0154	0.0080	0.0058	0.0270	0.0658	0.9303	0.0018	0.0164	0.0049	0.0013

MOROCCO	0.0474	0.0206	0.0119	0.0210	0.0384	0.0035	0.0392	0.0044	0.0439	0.0014	0.0098	0.9359	0.0097	0.0050	0.0220
BANGLADESH	0.0007	0.0024	0.0025	0.0004	0.0049	0.0029	0.0312	0.0127	0.0011	0.0009	0.0074	0.0022	0.9554	0.0009	0.0058
ARGENTINA	0.0042	0.0169	0.0016	0.0308	0.0368	0.0014	0.0057	0.0110	0.0075	0.0024	0.0068	0.0033	0.0007	0.9757	0.0015
PAKISTAN	0.0131	0.0077	0.0011	0.0159	0.0029	0.0029	0.0130	0.0116	0.0053	0.0027	0.0036	0.0133	0.0064	0.0075	0.9649

The foundations of the Diebold–Yilmaz framework, the FEVD table (5a), show the extent to which each of the given markets' forecast error variances can be explained/attributed to market shocks coming from the rest of the markets. The diagonal elements show the majority of error variances that are observed. These elements are substantially high across the countries (e.g., USA = 93.3%, Japan = 84.9%, China = 93.9%). This shows that in most cases, domestic shocks are the most substantial. This also shows that although domestic shocks are prevalent, there are considerable cross market spillovers. Canada, for instance, has 6.8% error variance from the UK and 4.1% from Saudi Arabia. On the other hand, Taiwan has 11.7% from Japan and 10.7% from the UK. Smaller frontier markets, particularly Morocco and Bangladesh, also show high domestic variance shares (93.6% and 95.5%, respectively), and still show substantial exposure to advanced economies' markets; demonstrating that global events can permeate to even the less integrated economies. Overall, the matrix of FEVD illustrates that the high volatility transmission and also the large emerging and developed markets are closely intertwined, while showing that the frontier economies are characterised by a level of insulation.

Table 5. Directional Spillovers: To, From, and Net

Market	To	From	Net	NetPct	To_avg	From_avg
USA	0.9724	0.7471	0.2253	7.018	0.0695	0.0534
JAPAN	0.3344	1.000	-0.6660	-20.74	0.0239	0.0715
HONG_KONG	0.4237	0.6866	-0.2630	-8.190	0.0303	0.0490
CANADA	1.370	0.7256	0.6441	20.06	0.0978	0.0518
UK	0.9843	0.6404	0.3440	10.71	0.0703	0.0457
CHINA	0.4254	0.4437	-0.0183	-0.5708	0.0304	0.0317
INDIA	0.7482	0.5016	0.2466	7.680	0.0534	0.0358
SAUDI_ARABIA	0.1585	0.4281	-0.2696	-8.399	0.0113	0.0306
TAIWAN	0.4197	0.6657	-0.2460	-7.662	0.0300	0.0476
UAE	0.2493	0.3077	-0.0584	-1.818	0.0178	0.0220
VIETNAM	0.4620	0.3333	0.1287	4.009	0.0330	0.0238
MOROCCO	0.2232	0.2782	-0.0550	-1.713	0.0159	0.0199
BANGLADESH	0.0926	0.0760	0.0166	0.5172	0.0066	0.0054
ARGENTINA	0.1150	0.1305	-0.0155	-0.4831	0.0082	0.0093
PAKISTAN	0.0935	0.1070	-0.0135	-0.4201	0.0067	0.0076

According to Table Five, the biggest net transmitter is Canada (Net = +0.644; 20.1%), due to the dominance of the Toronto Stock Exchange in North American capital and commodities financing. Following is the United Kingdom (+0.344; 10.7%), which is consistent with London being one of the world's financial centres, and then India +0.247; (7.7%), which reflects a fast-growing financial services industry. Interestingly, Japan, despite being a developed market, is the largest net receiver (–0.666; –20.7%). This is because of the high levels of home bias and risk aversion of institutional domestic investors. Also, as net receivers and as financial centres, Hong Kong and Saudi Arabia (–0.263; –0.270) show the same dependence on global financial systems.

Figure 3. Net Spillover (% of total absolute net)

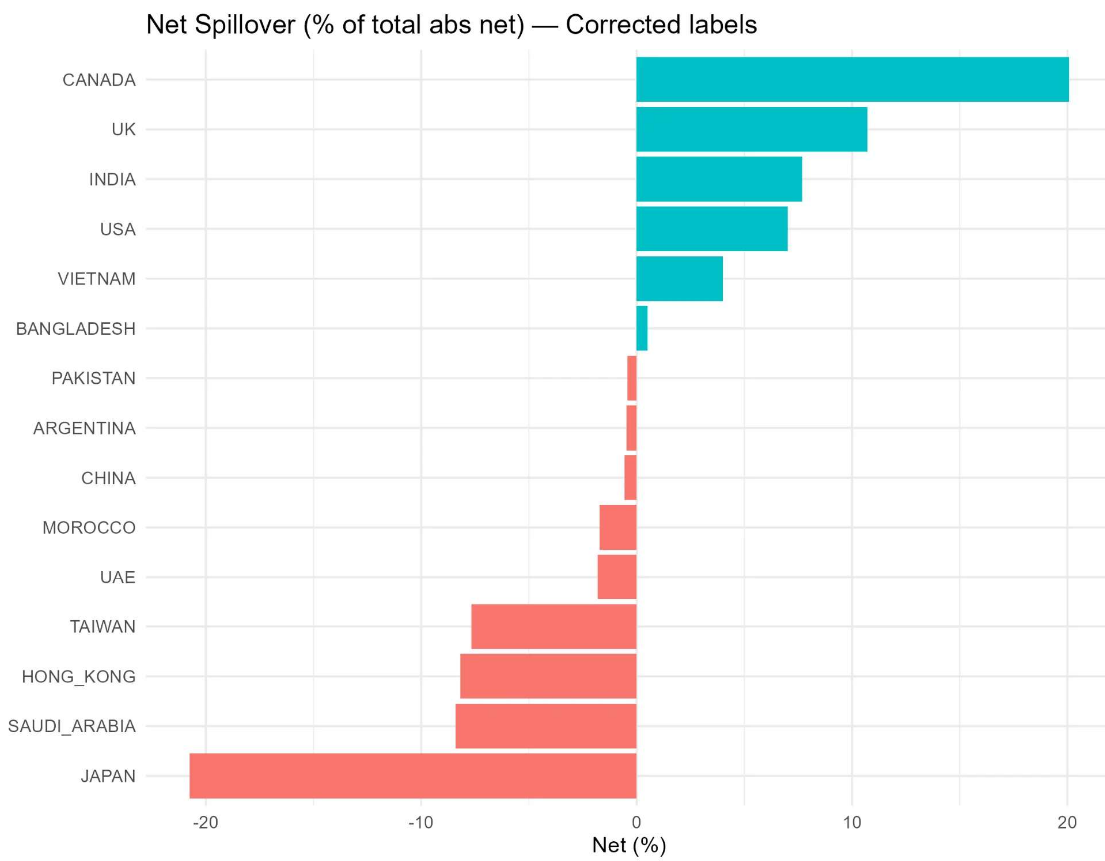
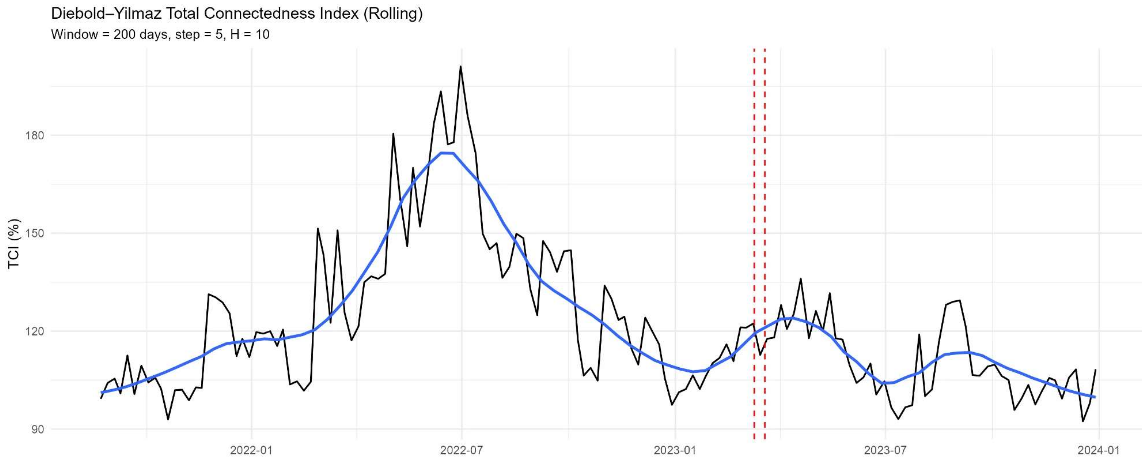


Figure 3 demonstrates each market's position as a net transmitter (positive values) or net receiver (negative values) of volatility spillovers. The findings show Canada (≈20%), the UK (≈11%), India (≈7%), and the USA (≈6%) as the most pronounced net transmitters. On the other hand, Japan has the most considerable negative net spillover (≈–20%), indicating its predominant position as a net receiver of volatility, followed by Saudi Arabia, Hong Kong, Taiwan, and the UAE.

4.7. Dynamic Connectedness Evolution

Figure 4. Diebold-Yilmaz Total Connectedness Index (Rolling)



The Total Connectedness Index (TCI) measures the volatility of forecast errors caused by spillover events. The TCI exhibits extreme temporal variability. Connectedness can be bidirectional. In such cases, TCI can be more than 100, indicating extreme interconnectedness. TCI can be more than 100 for intensity spillover cases (Diebold & Yilmaz, 2012). TCI peaked at 201% in mid-2022 during the Federal Reserve rate hikes and geopolitical instability. The events of SVB and Credit Suisse (March 2023) were low connectedness (115-120%) states with no considerable changes in TCI. This means that there was either a heightened level of systemic risk due to previous monetary restriction, or there were effective policies in place to mitigate the possibility of contagion. The December 2023 TCI trough (92.3%) illustrates the absence of correlation regime shifts with market stabilisation.

Table 6a. Summary Statistics of Rolling Total Connectedness Index (TCI)

Metric	Value
N_windows	147
Mean_TCI	121.345
Median_TCI	117.175
SD_TCI	22.42
Min_TCI	92.345
Min_Date	2023-12-18
Max_TCI	201.094
Max_Date	2022-06-30
NA_fraction	0

The TCI descriptive statistics over 147 rolling windows are presented in Table 6a. The mean (121.35%) and median (117.18%) show that spillover intensity was very high and indicative of interdependence across markets. The dispersion (SD = 22.42) shows that during episodes of stress, the volatility spillovers increased substantially while in calmer periods the return was closer to the long-term mean.

Table 6b. Peaks and Troughs of Rolling Total Connectedness Index (TCI)

Type	Rank	Date	TCI

Top	1.000	2022-06-30	201.09
Top	2.000	2022-06-13	193.42
Top	3.000	2022-07-06	185.93
Bottom	1.000	2023-12-18	92.34
Bottom	2.000	2021-10-21	92.97
Bottom	3.000	2023-07-12	93.07

In Table 6b, extreme cases of connectedness are presented. The largest TCI of 201.09% was observed on 30 June 2022, and this was succeeded by two further peaks during the summer of 2022, aligning with the period of aggressive global monetary tightening and heightened geopolitical tensions. In contrast, the extreme cases of TCI fell in late 2021 and in mid-2023, where TCI was observed at 92.35% on 18 December 2023. This suggests that the markets were relatively decoupled and that the volatility cross pressure had eased during this period.

Table 6c. Pre- and Post-Event Changes in Rolling Total Connectedness Index (TCI)

Event	EventDate	Pre_Mean_TCI	Post_Mean_TCI	Diff	p_value	Pre_N	Post_N
SVB_Collapse	2023-03-10	116.51	114.69	-1.817	0.5707	30.00	30.00
CreditSuisse_Crisis	2023-03-19	115.66	114.32	-1.339	0.6685	30.00	30.00

Table 6c illustrates the results of the event studies on the crises of SVB and Credit Suisse. The mean TCI averages pre-and post-event being compared in this case are statistically indistinguishable, with event impacts observed of -1.82 and -1.34 percentage points, respectively. This shows that while these shocks generated strong localized impacts of volatility (as discussed in the previous sections) on the interdependent markets, they did not significantly change the levels of systemic connectedness of the global equity markets.

4.8. Spillover Network Architecture

Figure 5. Net Spillover Network among Global Markets

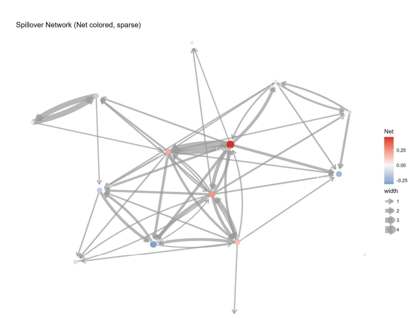


Figure five illustrates the topology of the networks of volatility transmission, where the size of the nodes corresponds to the magnitude of net spillover transfers and the colour code distinguishes transmitters (in red) and receivers (in blue). The network has a core-periphery structure; developed markets (USA, Canada, UK) and India constitute an interconnected core, with thick edge(s) indicating strong bilateral ties, whereas the periphery consists of frontier markets (Bangladesh, Morocco, Pakistan) with weak or limited connections. Shocks originating from core markets are quickly disseminated throughout the entire network, whereas disturbances from the periphery are not. The links between Canada and the UK and the USA and the UK are the most significant for transatlantic transmission, and the net outward arrows indicating Japan confirm Japan's position as a volatility sink, and illustrate that the primary transmission channels are the core markets.

5. Conclusion

The focus of this research is on developing spillover volatility in the aftermath of the crises of the 2023 Silicon Valley Bank collapse and the Credit Suisse crisis in 15 developed, emerging, and frontier equity markets. Focusing on GARCH (1, 1) volatility estimation, windows of event study, and spillover analysis of Diebold- Yilmaz, we document heterogeneity of crisis response. Advanced economies have increased volatility, but it normalised quickly, while emerging and frontier economies have responded differently. These responses are based on the liquidity, information insulation, and the quality of the institutions of the markets (Bekaert & Harvey, 2002; Diebold & Yilmaz, 2012).

According to the network analysis, the major transmitters are Canada, the United Kingdom and India; while Japan, Hong Kong and Saudi Arabia are the receiver's markets. Japan's position as a receiver of developed markets is a sign that its developmental stage is not a good predictor of network position (Forbes & Rigobon, 2002). Connectedness Index values are over 120% and this is a sign of extreme interdependence among markets, and there is no notable increase in connectedness that the banking crises have brought (Antonakakis et al., 2020). This means there is a good chance of systemic risk with effective measures that have been taken.

For regulators, the findings of this study highlight the need to consider systemic risk from a network perspective (Diebold & Yilmaz, 2012). Asymmetric patterns of contagion act in a contrary way to the diversification of portfolios that assume the correlation between crises is constant (Kaminsky et al., 2003). These restrictions include the focus on 15 equity markets, the GARCH(1,1) specifications and the use of equity markets. Additional classes of assets, time parameters, institutional parameters, and the use of multiple crises should feature in future research.

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Conflict of Interest

The authors state that there is no conflict of interest.

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