“Spillovers across global stock markets before and after the declaration of Russia’s invasion of Ukraine”

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SPILLOVERS ACROSS GLOBAL STOCK MARKETS BEFORE AND AFTER THE DECLARATION OF RUSSIA'S INVASION OF UKRAINE

Abstract

Since the financial meltdown, studies on systemic risk and financial contagion have gained currency. Events like the COVID pandemic and the Russian invasion of Ukraine have fueled such an importance. This study examines the impact of the invasion on volatility transmissions across major stock markets worldwide. The stock indices considered in this study are ASX 200, ESTOXX 40, FTSE 100, HNGSNG, NIFTY 50, NIKKIE, and S&P 500. The work uses Vector Auto Regression (VAR) to study the transmission of returns. Later, the work performs Dynamic Conditional Covariance-Generalized Auto Regression Conditional Heteroskedasticity (DCC-GARCH) on the residuals where the transmission of returns was significant. The DCC-GARCH (E-GARCH) shows that all the asymmetric transmissions are negative. The study finds that co-movements of stock returns for the following pairs: ESTOXX 50-S&P 500, NIFTY 50-FTSE100, NIFTY 50-NIKKIE, NIKKIE-ESTOXX 50, S&P 500-NIFTY 50, and SP500-HNGSNG significantly intensified after the declaration of invasion. Such intensification of co-movements does establish the contagion effect triggered by invasion. The study shows that ESTOXX 50, which has the closest geographical proximity to the war zone, happens to be the highest generator of spillovers.

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INTRODUCTION

Since the declaration of the Russian invasion of Ukraine, the stock markets have seen upheavals in their performances. The stock markets across the globe have seen slumps, while countries heavily reliant on crude oil and related products saw a significant weakening of their exchange rate as compared with the USD. Today, in this highly interconnected world, a war between two countries has varying degrees of effect worldwide. In the past, the world has witnessed changes in spillovers across the global stock market owing to trade connections, the dependence of participating countries on crude oil, etc. The wars could be the US war in Vietnam, the Kuwait war in 1991, the Iraq war in 2003, etc. One major repercussion is that countries facing severe debt crises have been further burdened by rising inflation due to the war. Sovereign defaults can induce and amplify the risk globally. Therefore, it becomes a matter of importance to study the dynamics of spillovers across various asset classes and markets during such a period. This work studies spillovers amongst the major global stock markets (ASX 200, ESTOXX 50, FTSE 100, HNGSNG, NIFTY 50, NIKKIE, and S&P 500) before the Russian invasion of Ukraine was declared and how they changed after the declaration of war on volatility transmissions.

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1. LITERATURE REVIEW

The theoretical literature in this respect discusses the mechanisms of the spread of financial contagion. The empirical literature provides empirical evidence for the propagation of risks/financial shocks across various sectors and regions of the globe for the same type of sector, considering various measures of risk while studying the contagion. Some works discuss various numerical methods to establish the contagion. The literature can be classified into the following aspects: a) Mechanisms/causes behind the propagation of financial contagion, b) Challenges in studying spillovers and measures devised to address these challenges, c) Empirical evidence that observes the contagion across various sectors and regions, d) Repercussions of spillovers, and e) Measures to deal with systemic risk.

Financial institutions nowadays open themselves to multiple sources of funding and investment; they do diversify risk but, all the same, create new pathways of propagation of financial distress (Glasserman & Young, 2016). Zhao et al. (2018) attribute the spillovers to capital flows across markets, sectors, or countries. On the other hand, Mieg (2020) propounds that volatility transmits systemic risk through reactivity (response by stakeholders to economic forecasts), reflexivity (interaction of functions and recursivity (transmission of risks through recursive functions). Fama-French risk factors contribute a major portion to the propagation of systematic risk (Yang et al., 2018). Literature and practice assert that financial interconnectedness has increased the transmission of financial risk across the globe and in various sectors, especially during events like war, financial crisis, etc. For example, Bordo and Murshid (2000) and Billio and Caporin (2010) assert that such transmissions increase/exacerbate during crises like global financial crises, wars, etc. Moreover, the contagion between the same entities can vary over time due to events (Kocarslan, 2019). Scholars have found spillover effects among different equity markets during COVID-19 (Siriopoulos et al., 2021; Spulbar et al., 2022; Zeng & Lu, 2022) and among different asset classes (Nguyen, 2023). Domestic inflation and debt conditions may further contribute to volatility spillovers (Samitas et al., 2017) and affect domestic interest rates (Ghosh, 2020). Evidence shows that volatility transmission amongst the currency markets increased post-financial crisis of 2008 in Brazil, India, Russia, and South Africa Mittal et al. (2019). Similarly, it has been found that the systemic nature of interconnectedness is higher during a crisis. For example, Louati and Firano (2022) conducted a study on how exports and imports impact the stock markets of the participating countries. COVID-19 did play its role in triggering and changing spillovers across various global asset classes. Choi (2022) establishes contagion statically and dynamically across multiple sectors in the USA during the COVID-19 pandemic. The literature provides empirical evidence on how events can shape and change the volatility transmissions across regions and markets/asset classes.

Evidence of spillovers from crude oil to various indices in the Indian stock market exists, as per Singhal and Ghosh (2016). Similarly, Chen and Zhang (2023) studied the impact of crude price shocks on stock markets worldwide. On the other hand, Jammazi et al. (2017) establish a bi-directional causality between crude and stock. Performing a study on spillover amongst liquidity risk, interest rate risk, real estate market risk, and market risk of an economy, Cotter and Surlaaht (2019) apply Diebold and Yilmaz's (2012) measure for spillover. Emulating too big to fail, a concept of too interconnected to fail has been used by Zihui and Yinggang (2020) to understand and address systemic risk due to financial shocks across various sectors globally. The copula method helps in accounting for asymmetric impacts, as per Zhu et al. (2021). Mutual causalities have not been explored in cases where dynamic conditional correlations have been considered. Amongst the latest works like Chancharat and Sinlapates (2023), Chen and Zhang (2023), and Chancharat and Sinlapates (2023) apply methods like DCC-GARCH and BEKK GARCH to study crude oil volatility spillovers on stock markets in Asia-Pacific. The literature demonstrates spillovers across global regions and asset classes.

Issues like mutual causality complicate the study of the phenomenon of transmission of risk. Various measures of risk transmission and numerical methods have been adopted to address the complexities while studying the transmission of risk across the sector and various geographical regions. Literature finds various tools that were adopted to address these challenges. Developing a metric to assess risk-sharing in a globalized economy, Flood et al. (2011) observe an improvement in this measure with the progression of globalization. Forecast error variance decomposition through Vector Auto Regression can serve as a foundation to study mutual causality in transmissions, as Diebold and Yilmaz (2012) have assessed volatility spillover and the transmission of contagion. Implied volatility as a measure of volatility was used to study contagion amongst global stock markets. For example, Gang and Zhang (2012) use implied volatility to study the connectedness between HANG SENG and Nasdaq-100. The work finds that the implied volatilities of US stock markets impact the implied volatilities of HANG SENG before the financial crisis. Introducing the concept of realized semi-variance on both negative and positive sides, Barunik et al. (2016) aim to address the asymmetric spillovers within the VAR family. In fact, Li (2021) uses Barunik et al.'s (2016) measure to explore asymmetric volatility spillovers across the US, Germany, Brazil, JAPAN, Italy, France, UK, Canada, China, and Indian stock markets.

Events often have an impact that is not limited to a particular geographical area in this connected world. The very changing landscape of contagion poses a challenge in the form of dynamic volatility transmission. The literature finds various methods and measures to study event-driven spillovers. Applying Capital Asset Pricing Models and utilizing beta values from eight European stock markets, Alexandridis and Hasan (2017) investigate the spillover effect of the 2008 financial crisis. They find that spillover increases with betas, arrived using higher time horizons, and the contagion amongst betas is high during the crisis period. Elsayed. et al. (2021) use the Time-Varying Parameter VAR (TVP-VAR) to establish the interconnectedness among the volatilities of returns on bitcoin and the volatilities of returns on traditional assets like crude oil, gold, etc., during the COVID pandemic. Similarly, Umar et al. (2022) use TVP-VAR to observe that European financial markets were net transmitters during the Russian invasion of Ukraine. Studies find that during the Russian invasion of Ukraine Crude oil and Metals are net shock contributors to other Russian sectors (Costola & Lorusso, 2022). Proximity to the war zone has a declining effect on stock market returns, as per Federales et al. (2022). Fat-tailed data poses yet another problem in studying event-driven spillovers. Conditional autoregressive value at risk (CAViaR) is used as a measure of risk to address heavy-tailed data by Engle and Manganelli (2004).

The cascading effect is one serious consequence of contagion. Various types of risks of different entities in the capital markets exacerbate each other, which can lead to the failure of an economic system (concept of "Risk Systemicity" as propounded by Ackermann et al. (2007)). Extending the concept of "Risk Systemicity" and studying the relationship between interconnectedness and the propagation of systemic risk, Minoiu et al. (2014) and Centeno et al. (2015) concur that interconnectedness has a strong association with global financial risk. Such financial interconnectedness in an economic system can cause default at small levels to get aggregated and amplified higher (Battiston et al., 2016). Similarly, Raavinutahala et al. (2023) discuss the interrelations amongst liquidity, credit, and market risks of the Indian banking system. Financial contagion has a long-lasting impact on the decision-making of short- and long-term investors, governments, and international institutions (Ang & Bekaert, 1999; Dooley & Hutchison, 2009). The literature in this context highlights that contagion can wreak havoc on the economic system in an interconnected world, thus stressing the importance of studying contagion/transmission of risk in the interconnected world triggered by events like the COVID-19 pandemic, global financial crisis, wars, etc.

Literature provides five steps for mitigating systemic risks (Besar et al. (2010)). These steps include: a) Ensuring that capital requirements are structured to avoid instigating the rapid sell-off of assets; b) Minimizing moral hazard by providing banking support through contingent capital arrangements; c) Cultivating managerial awareness of the systemic impact arising from the interconnectedness of participating entities; d) Introducing redundancy in over-the-counter markets for securities and derivatives; and e) Promoting financial transparency.

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The survey has not found a study on spillovers amongst stock markets when the conditional correlations can change over time with conditional volatilities, especially in the case of extreme events like war. Therefore, this work studies how returns and volatility transmission in global stock markets behaved before and after the declaration of the Russian invasion of Ukraine in order to see how the Russian invasion of Ukraine impacted the spillovers over global stock markets.

2. METHODS

Daily data on respective stock market indices was collected from the Yahoo finance website. The time frame of data collection was from April 1, 2021 to February 28, 2023 on a daily basis. The stock markets considered in this work are India, Europe, the UK, the USA, Australia, Japan, and China. Stock index data was collected daily from April 1, 2021 to February 28, 2023. The work uses NIFTY 50 as a proxy for Indian stock market returns, which is in line with Kumar and Mishra (2020). Taking from Bohl et al. (2008), the study uses ESTOXX 50 as a proxy for European stock market returns. FTSE 100 is used as a proxy for UK stock markets in line with Gao et al. (2019). Following Gibson and Mougeot (2004), the S&P 500 is considered a proxy for USA stock market returns. Adopting Smales (2017), this work uses ASX 200 as a proxy for Australian stock market returns. Following Apergis and Apergis (2020), this work uses HANG SENG as a proxy for China's stock market returns. Taking from Abbas et al. (2013), this work uses NIKKIE as a proxy for Japanese stock market returns.

The daily return on the stock indices is taken as indicated by Equation (1)

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}, \tag{1}$$

where R_t is the daily return on the stock index, P_t is the closing price of the stock index on day t, and P_{t-1} is the closing price of the stock index on a trading day before t.

The time series data on daily returns of NIFTY-50, NIKKIE, HNGSNG, ESTOXX 50, FTSE 100 100, SP500, and ASX 200 shows stationarity at a significance level of one percent as per the Adisson Dickey-Fuller test, indicating unrestricted VAR can be used on the returns data. Seventh Lag is the optimal lag per Schwartz Criterion (SC) and Akaike Information Criterion (AIC) for the unrestricted VAR. A bi-variate model of unrestricted VAR is represented by equations (2) and (3)

$$Y_t = \sum_{i=1}^{n} \beta_i Y_{t-i} + \sum_{i=0}^{n} \alpha_i X_{t-i} + \varepsilon_y, \tag{2}$$

$$X_t = \sum_{i=1}^{n} \gamma_i X_{t-i} + \sum_{i=0}^{n} \delta_i Y_{t-i} + \varepsilon_x, \tag{3}$$

where X and Y are the endogenous variables, i is the lag number, and t is the timeline. α, β, γ, δ are the regression parameters, and ε is the corresponding error term.

Once the unrestricted VAR is performed, the residuals are obtained and tested for autocorrelation and heteroskedasticity. The Portmanteau Q Statistic indicates the absence of autocorrelation amongst the VAR residuals of the stock return. Table 1 shows the instances where kurtosis is greater than three, which implies fatter tails and calls for the application of dynamic volatility to study the spillovers. Moreover, the Generalised Auto Regressive Conditional Heteroskedasticity (GARCH) test shows heteroscedasticity of the residuals. This does justify the application of multivariate GARCH to study the volatility transmissions. Engle et al. (1990) and Bollerslev (1990) present the CCC-GARCH. However, conditional correlations may vary with time if they are a function of conditional volatility. Engle and Sheppard (20010) developed DCC-GARCH to address the dynamic conditional correlations. Therefore, the work adopts DCC-GARCH. Within the DCC-GARCH, Exponential-GARCH (E-GARCH) and Symmetric-GARCH (S-GARCH) have been used to compare the results. The general form of the DCC-GARCH model is represented by equations (4) to (8).

$$r_t = \mu_t + a_t, \tag{4}$$

$$a_t = H_t^{\frac{1}{2}} z_t, \tag{5}$$

$$H_t = D_t R_t D_t, \tag{6}$$

where r_t is kx1 vector of log-returns of k assets at time t; a_t is kx1 vector of mean corrected returns of k assets at time t; $H_t^{1/2}$ any nxn matrix such that; H_t is the conditional varaince matrix of a_t; z_t is kx1 vector of independent and identically distributed errors such that $E[z_t] = 0$ and $E[z_t z_t^T] = I$; Dt is kxk dignal matrix of standard deviations of a_t at time t; R_t is kxk is the time-variant conditional correlation matrix of a_t.

The equations that determine R_t are (6) and (7)

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{7}$$

$$Q_t^{i,j} = (1-\theta_1-\theta_2)\cdot Q^* + \theta_1(\mu_{it-1}\mu_{jt-1}) + \theta_2(Q_{t-1}^{i,j}), \tag{8}$$

where $Q_t^{i,j}$ is the correlation between series i and j at time t; μ_{it-1}, μ_{jt-1} are the conditional mean of series i, j at time $t-1$; Q^* is the unconditional covariance between series i,j the scalar parameters θ_1 and θ_2 are equal to or greater than zero and satisfy the condition: $\theta_1 + \theta_2 < 1$.

Equations (9) to (11) illustrate the S-GARCH model, while equation (12) gives the variance under the E-GARCH model. Equation (13) defines the conditions to be met for the S-GARCH and E-GARCH processes.

$$y_t = \beta y_{t-1} + \mu_t, \tag{9}$$

$$\mu_{t=}\varepsilon_t\sqrt{h_t}, \tag{10}$$

$$h_t = \gamma_0 + \sum_{i=1}^{p}\delta_i h_{t-1} + \sum_{j=1}^{q}\gamma_j + \mu_{t-j}^2. \tag{11}$$

Equation (9) is an autoregression model where $u_t \sim N(0, \sigma_t^2)$ and σ_t^2 are not constant but change over time and depend on past history. The term h_t stands for the systematic variance that changes over time; $\boldsymbol{\varepsilon}_t$ is white noise and follows standard normal with mean zero and variance unity.

Where p is the lag order of variance; q is the lag order of residual error

$$\log(\mathrm{h_t}) = \gamma_0 + \sum_{j=1}^{q}\lambda_j\left|\frac{\mu_{t-j}}{\sqrt{h_{t-j}}}\right| + \sum_{j=1}^{q}\gamma_j\frac{\mu_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p}\delta_i\log(h_{t-i}), \tag{12}$$

$$\gamma_0 > 0,\quad \delta_i > 0,\quad \gamma_j > 0 \quad \text{and} \quad \delta_i + \gamma_j < 1. \tag{13}$$

δ_i is the coefficient term of conditional variances; γ_j is the coefficient term of residual errors; γ_0 is the constant intercept; h_t is the conditional variance at time t; μ_t is the conditional mean at time t; y_t is the return on the asset class at the time t; β is the linear regression coefficient.

3. RESULTS

Table 1 shows that the kurtosis is greater than three, which implies fatter tails and calls for the application of dynamic volatility to study the spillovers. The Jarque-Bera test results shown in Table 1 indicate the data does not follow the normal distribution, ratifying the application of dynamic volatilities to study the spillovers.

The results of VAR on stock returns are shown in Table 2. The VAR shows significant spillover of returns from ESTOXX 50-FTSE 100, ESTOXX 50-NIFTY 50, ESTOXX S&P 500,

Table 1. Descriptive statistics

	Returns of						
	ASX 200	**ESTOXX 50**	**FTSE 100**	**HNGSNG**	**NIFTY 50**	**NIKKIE**	**S&P 500**
Mean	1.70E–05	8.75E–05	0.0002	–0.0004	0.0005	–6.73E–05	2.55E–06
Median	9.76E–06	0.0003	0.0004	–0.0006	0.0005	0.0003	0.0000
Maximum	7.78E–05	0.0312	0.0167	0.0378	0.0350	0.0178	0.0234
Minimum	0.0000	–0.0269	–0.0181	–0.0285	–0.0595	–0.0191	–0.0300
Standard deviation	1.25E–05	0.0060	0.0042	0.0080	0.0111	0.0057	0.0060
Skewness	1.7225	–0.1448	–0.5176	0.4897	–0.8867	–0.0892	–0.3716
Kurtosis	5.6292	6.4784	5.5834	5.9599	6.7598	3.8146	5.7558
Jarque– Bera	313.0011	203.0498	129.0950	162.0070	288.0097	11.5889	135.7754
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0030	0.0000

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Table 2. Vector Auto Regression results on stock returns

	Returns of						
	ASX 200	**ESTOXX 50**	**FTSE 100**	**HNGSNG**	**NIFTY 50**	**NIKKIE**	**S&P 500**
ASX 200200(–1)	–0.25170***	–16.26623	–4.25021	–22.34762	30.64390	–10.65901	–3.90655
ASX 200200(–2)	–0.16871***	11.52905	3.01815	–3.56453	–57.84319	–22.32721	–3.94590
ASX 200200(–3)	–0.21544***	–22.15477	–15.86668	28.15788	–42.51633	–33.30844	–0.98270
ASX 200200(–4)	–0.01727	–27.31203	–2.81985	28.45004	–53.85319	–18.27335	–29.32320
ASX 200200(–5)	0.02391	–4.73690	9.63516	45.61040	15.08249	–7.52739	–11.76735
ASX 200200(–6)	–0.05781	16.88820	17.06434	43.50148	61.84847	–31.14637	–29.65183
ESTOXX(–1)	–0.00028	0.09050	0.14311	0.35996**	0.68394***	0.58545***	0.35868***
ESTOXX(–2)	–0.00007	0.15722	0.07761	0.17356	–0.27758	0.14040	0.22577**
ESTOXX(–3)	–0.00006	0.19074	0.15725**	–0.04053	0.4004**	0.2175**	0.13357
FTSE 100(–1)	0.00038	–0.14760	–0.2227**	–0.06973	–0.47944	–0.16985	–0.00194
FTSE 100(–2)	–0.00032	–0.17410	–0.14866	0.07786	0.48531	–0.02644	–0.01599
FTSE 100(–3)	0.00007	–0.20473	–0.2043**1	0.35927*	–0.31942	–0.15488	–0.01546
FTSE 100(–4)	0.00006	–0.04404	–0.06004	0.33346*	–0.18637	–0.22519	0.18994
FTSE 100(–5)	0.00014	0.14414	0.03266	0.16487	0.02362	–0.03587	0.07968
FTSE 100(–6)	0.00016	0.15450	0.00934	0.32618*	–0.40980	–0.05288	0.00947
FTSE 100(–7)	–0.00028	0.21355	0.08300	0.46314**	0.21290	–0.03347	0.10224
HNGSNG(–1)	–0.00001	–0.1082**	–0.02427	0.01538	–0.05030	0.03001	–0.03382
HNGSNG(–2)	0.00001	–0.07094	–0.04589	–0.18693***	–0.14718	–0.01796	–0.03538
HNGSNG(–3)	–0.00004	–0.02151	–0.01491	0.01312	–0.03218	–0.02118	–0.01848
HNGSNG(–4)	–0.00007	0.04278	0.02195	–0.08931	–0.09728	–0.04036	–0.01631
HNGSNG(–5)	0.00003	–0.07949	–0.05430	–0.05249	–0.11931	–0.06596	0.00766
HNGSNG(–6)	–0.00009	0.09157	0.03619	0.02837	–0.00513	0.00390	0.00625
HNGSNG(–7)	0.00000	–0.1046**	–0.0832**	0.03634	–0.06638	–0.01645	0.01657
NIFTY(–1)	–0.00010	–0.01615	–0.00672	–0.03697	–0.07492	–0.06953**	0.01663
NIFTY(–2)	0.00005	–0.1137***	–0.0550**	0.01672	–0.1431**	–0.05406	–0.05990
NIFTY(–3)	–0.00003	0.08814**	0.0777***	0.08390	0.10619	0.04686	0.02394
NIFTY(–4)	0.00011	–0.04014	–0.00135	–0.05089	0.00600	0.00807	–0.02888
NIFTY(–5)	–0.00004	0.1046***	0.0596**	0.07318	0.05015	0.1281***	0.03752
NIFTY(–6)	–0.00008	–0.04157	–0.01576	–0.00301	–0.0941	–0.1017***	–0.0682*
NIKKIE(–1)	0.00013	–0.03536	–0.03334	–0.1414	–0.0848	–0.1535**	0.05513
NIKKIE(–2)	0.00002	–0.05669	–0.02144	0.06585	–0.02120	0.01616	–0.02292
NIKKIE(–3)	0.0003**	–0.06062	–0.10832	–0.17552	–0.26325*	0.02045	0.03742
NIKKIE(–4)	–0.00013	–0.02579	–0.07478	–0.06676	–0.07707	–0.04745	–0.08783
NIKKIE(–5)	–0.00021	–0.10857	–0.05038	–0.02423	0.2357*	–0.02397	–0.04664
NIKKIE(–6)	–0.00004	–0.04934	–0.00240	–0.06562	0.06089	0.03173	0.00707
NIKKIE(–7)	–0.0001	–0.06866	–0.05649	–0.14885	–0.2257*	–0.05344	–0.02426
SP500(–1)	0.00011	0.07775	0.03514	–0.00048	0.11625	–0.01033	–0.1947***
SP500(–2)	0.00002	0.09777	0.06131	–0.08220	0.27273**	–0.05684	–0.1567***
SP500(–3)	–0.0003**	–0.04375	–0.00333	–0.13701	–0.03971	–0.07415	–0.09304
SP500(–4)	–0.00008	–0.04535	0.01747	0.01516	0.09959	0.02732	0.03711
SP500(–5)	–0.00017	–0.00555	0.01186	–0.09077	–0.03282	–0.03995	–0.03817
SP500(–6)	0.00007	–0.05470	–0.05297	–0.27371***	0.01321	–0.12199	–0.15322
SP500(–7)	–0.00021	0.06852	0.03089	–0.03308	0.06434	0.01816	–0.04310
C	0.00003***	–0.00028	–0.00010	–0.00356	–0.00001	0.00138	0.00163

Note: * indicates significance at 0.1, ** indicates significance at 0.05, and *** indicates significance at 0.01. The values in brackets show the T-statistic.

HNGSNG-ESTOXX 50, HNGSNG-FTSE100, NIFTY 50-FTSE, NIFTY 50-NIKKIE, NIKKIE-ASX 200, NIKKIE-ESTOXX 50, NIKKIE-FTSE 100, S&P 500-ASX200, S&P 500-HNGSNG, and S&P 500-NIFTY 50 to be significant. The VAR residuals shown in Figure 1 show clustering, indicating the ARCH effect. The ARCH-LM test shows the presence of heteroskedasticity, and the Portmonteau Q-Statistic indicates the absence of serial correlation amongst the residuals (refer to Table 3). Therefore, the study proceeds to perform the DCC-GARCH on the VAR residuals where the causality has been found significant. The study performs two versions of DCC-GARCH, DCC-GARCH (S-GARCH) and DCC-GARCH (E-GARCH), and compares the results.

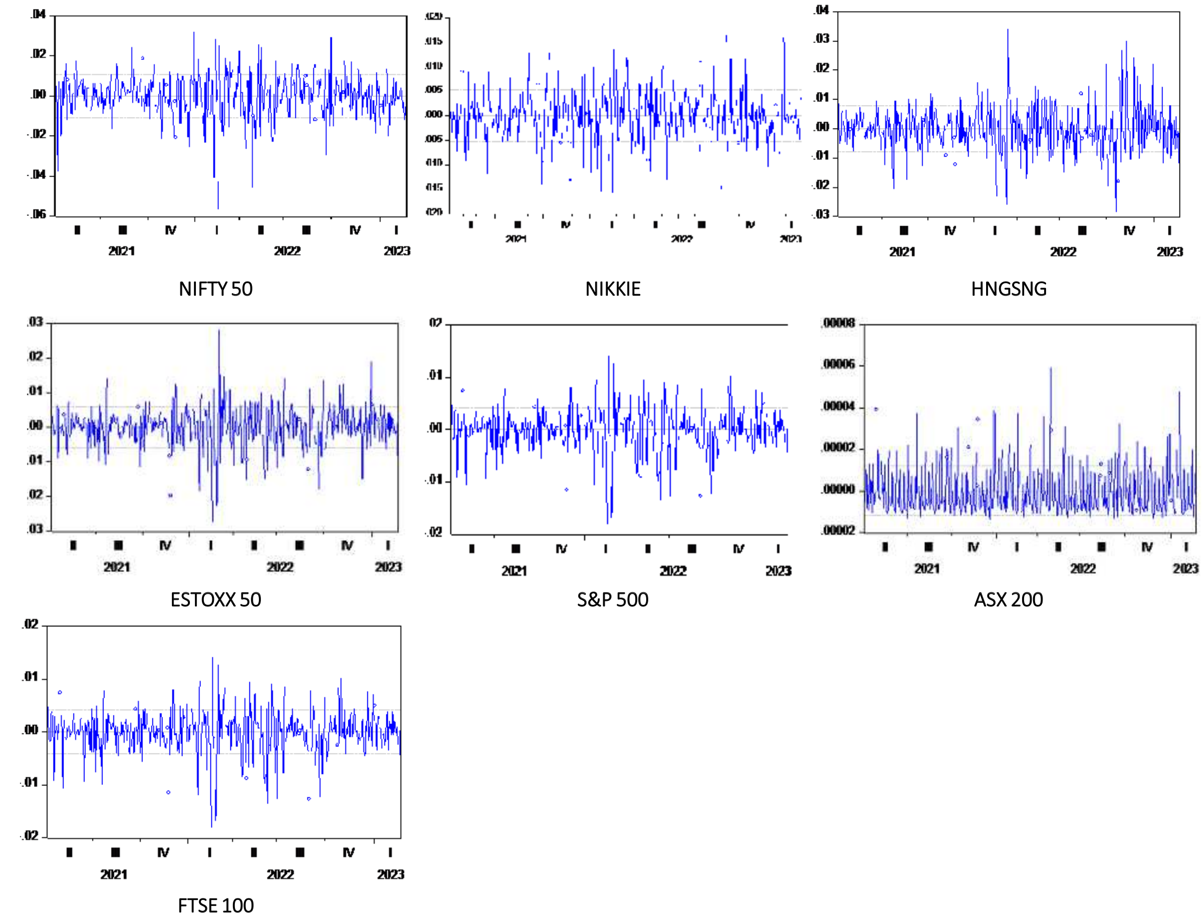

Figure 1. VAR residuals of stock market returns

Table 3. Autocorrelation and GARCH test results of spillovers

	Serial Correlation and Heteroskedastic tests on Returns of						
	SP500–ASX 200	**NIKKIE–ASX 200**	**HNGSNG–ESTOXX 50**	**NIKKIE–ESTOXX 50**	**ESTOXX 50–FTSE 100**	**HNGSNG–FTSE 100**	**NIFTY 50–FTSE 100**
	Coeff	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**
LM-Test	43.49	52.388	44.7669	52.384	43.3839	40.5801	0.4865
ARCH-Test	134.8***	98.5193**	244.5492***	186.473***	203.9264***	221.8311***	18.0.962***
	NIKKIE–FTSE 100	**ESTOXX 50–NIFTY–50**	**S&P 500–NIFTY 50**	**NIFTY 50–NIKKIE**	**ESTOXX S&P 500**	**SP500–HNGSNG**	
	Coeff	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	
LM-Test	53.0314	47.048	50.0116	61.404	46.2883	36.0646	
ARCH-Test	154.3722***	197.8318***	156.0121***	170.9456***	272.46***	165.2603***	

Note: * indicates significance at 0.1, ** indicates significance at 0.05, and *** indicates significance at 0.01.

NIKKIE and FTSE 100 are the highest recipients of contagion (two each out of nine cases). Interestingly, the contagion betwixt NIKKIE and ESTOXX 50 is found to be mutual. For the pairs ESTOXX 50-HNGSNG, FTSE 100-HNGSNG, S &P 500 – ASX-200, NIKKIE-ASX 200, HNGSNG-FTSE 100, S &P 500 –HNSGSNG, ESTOXX 50-NIFTY-50, S&P 500-NIFTY 50, NIFTY 50-NIKKIE, and ESTOXX-S&P 500 Θ_1 is insignificant, while Θ_2 is significant. That shows that only long-term persistent volatilities significantly impact the dynamic conditional correlations. For the pairs NIKKIE-ESTOXX 50, NIFTY 50-FTSE 100, and NIKKIE-FTSE 100, both Θ_1 and Θ_2 are significant, indicating that short-run and long-run persistence effects significantly impact these pairs' volatilities.

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Table 4. Spillover results of DCC-GARCH (S-GARCH)

	Spillover pairs of Residuals of Vector Autoregression														
	SP500–ASX 200	**NIKKIE–ASX 200**	**HNGSNG–ESTOXX 50**	**ESTOXX 50–FTSE 100**	**HNGSNG–FTSE 100**	**NIFTY 50–FTSE 100**	**NIKKIE–FTSE 100**	**ESTOXX 50–HNGSNG**	**FTSE 100 –HNGSNG**	**S&P 500–HNGSNG**	**ESTOXX 50–NIFTY 50**	**S&P 500–NIFTY 50**	**ESTOXX 50–NIKKIE**	**NIFTY 50–NIKKIE**	**ESTOXX S&P 500**
	Coeff	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**
γ_0	9.47E–13	9.47E–13	6.30E–06	2.34E–06	2.34E–06	2.34E–06	2.34E–06	2.82E–07	2.82E–07	2.82E–07	1.66E–06	1.7E–06	1.98E–07	1.98E–07	1.92E–07
δ	0.05***	0.05***	0.0501***	0.0503***	0.0503***	0.0503***	0.0503***	0.0511***	0.0908***	0.0502***	0.0514***	0.0514***	0.0505***	0.0505***	0.0502***
λ	0.9***	0.9***	0.9***	0.9001***	0.9001***	0.9001 ***	0.9001***	0.9464***	0.902***	0.9***	0.9005***	0.9005***	0.9001***	0.9001***	0.9***
Θ_1	0.0000	0.0000	0.0000	0.0427	0.0000	0.0056	0.0513	0.0000	0.0000	0.0074	0.0116	0.0000	0.0233	0.0000	0.0000
Θ_2	0.9507***	0.9028***	0.9102***	0.918***	0.9981***	0.893***	0.7986***	0.9131***	0.9981***	0.9577***	0.915***	0.9209***	0.85***	0.9644	0.9079***
AIC	26.664	–26.861	–14.348	–16.188	–15.048	–14.209	–15.456	–14.348	–15.042	–14.377	–13.591	–13.481	–14.722	–13.658	–14.665

Note: * indicates significance at 0.1, ** indicates significance at 0.05, and *** indicates significance at 0.01.

Table 5. Spillover results of DCC-GARCH (E-GARCH)

	Spillover pairs of Residuals of Vector Autoregression														
	S&P 500–ASX 200	**NIKKIE–ASX 200**	**HNGSNG–ESTOXX 50**	**ESTOXX 50– FTSE 100**	**HNGSNG–FTSE 100**	**NIFTY 50–FTSE 100**	**NIKKIE–FTSE 100**	**ESTOXX 50–HNGSNG**	**FTSE 100 –HNGSNG**	**S&P 500–HNGSNG**	**ESTOXX 50–NIFTY 50**	**S&P 500–NIFTY 50**	**ESTOXX 50 –NIKKIE**	**NIFTY 50–NIKKIE**	**ESTOXX S&P 500**
	Coeff	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**	**Coeff**
γ_0	–.0007	–0.0007	–0.966	–0.0271**	–0.0271**	–0.0271**	–0.0271**	–0.9914***	–0.9914***	–0.9914***	–0.9166***	–0.9166***	–0.9501	–0..9501	–0. 3700***
γ	0.05	0.05	–0.0143	–0.0988*	–0.0988*	–0.0988*	–0.0988*	–0.1381***	–0.1381***	–0.1381***	–0.1171***	–0.1171***	–0.042	–0.0420	–0.1152***
δ	0.9***	0.9***	0.9002***	0.9971***	0.9971***	0.9971***	0.9971***	0.9001***	0.9001***	0.9001***	0.9015***	0.9015***	0.9003***	0.9003***	0.9647***
λ	0.1005	0.1005	0.7002	0.1586***	0.1586***	0.1586***	0.1586***	0.1348***	0.1348***	0.1348***	0.1323***	0.1323	0.295	0.2950	0.0551***
Θ_1	0.8674***	0.0000	0.0000***	0.0415**	0.017*	0.009**	0.0748**	0.0000	0.1887***	0.023	0.0741	0.0000	0.0375	0.0000	0.0344
Θ_2	0.1234	0.9339***	0.9303***	0.8824***	0.0000	0.8999***	0.8104***	0.9303***	0.0978	0.8991***	0.3739***	0.9149***	0.837***	0.9359***	0.0000
AIC	–6.833	–7.2873	–14.825	–16.983	–15.598	–15.079	–16.275	–14.825	–15.495	–14.754	–14.402	–14.226	–15.548	–14.46	–15.666

Note: * indicates significance at 0.1, ** indicates significance at 0.05, and *** indicates significance at 0.01.

Table 6. Spillover results of DCC-GARCH (S-GARCH)

Stock Indices pairs where returns spillover are significant	T-test based on results of DCC-GARCH (S-GARCH)					T-test based on results of DCC-GARCH (E-GARCH)				
	Mean Correlation Coefficient before Invasion	Mean Correlation Coefficient after Invasion	Variance of Correlation Coefficient before Invasion	Variance of Correlation Coefficient after Invasion	T-statistic	Mean Correlation Coefficient before Invasion	Mean Correlation Coefficient after Invasion	Variance of Correlation Coefficient before Invasion	Variance of Correlation Coefficient after Invasion	T-statistic
ESTOXX 50 – FTSE 100	0.7965	0.8094	2.25E–03	1.73E–03	–2.83***	0.7798	0.7783	1.05E–03	1.91E–03	0.40
ESTOXX 50 – NIFTY 50	0.5303	0.5348	2.32E–04	6.00E–04	–2.20**	0.5255	0.5263	2.52E–03	3.01E–03	–0.14
ESTOXX – S&P 500	0.4826	0.4826	2.52E–16	1.66E–16	2.27**	0.4781	0.4781	1.53E–16	4.16E–16	13.06***
HNGSNG – ESTOXX 50	0.3254	0.3254	6.65E–15	4.96E–15	–1.0984	0.3119	0.3119	1.89E–15	2.25E–15	0.3007
HNGSNG – FTSE 100	0.3224	0.3224	6.52E–17	9.07E–17	1.2369	0.3136	0.3064	3.20E–03	3.44E–03	1.2302
NIFTY 50 – FTSE 100	0.4647	0.4666	6.46E–05	1.07E–04	–2.032**	0.4710	0.4755	1.86E–04	3.24E–04	–2.78***
NIFTY 50 – NIKKIE	0.3888	0.3888	2.71E–15	3.58E–15	–8.79***	0.3977	0.3977	1.53E–16	4.16E–16	–5.42***
NIKKIE – ASX 200	0.0940	0.0940	2.74E–17	2.32E–17	–0.33	–0.0127	–0.0127	1.36E–14	3.29E–18	5.79***
NIKKIE – ESTOXX	0.3478	0.3340	2.08E–03	1.77E–03	3.10***	0.3751	0.3512	3.59E–03	4.11E–03	3.80***
NIKKIE – FTSE 100	0.3361	0.3221	8.03E–03	8.60E–03	1.5194	0.3674	0.3300	2.02E–02	2.49E–02	2.46**
S&P 500 – NIFTY 50	0.4003	0.4003	3.05E–15	3.66E–15	–7.10***	0.4204	0.4204	1.61E–18	2.33E–18	–6.94***
SP500 – ASX 200	–0.0168	–0.0168	2.62E–16	2.78E–16	16.25***	–0.0022	–0.0016	3.10E–02	2.07E–04	–0.0472
SP500 – HNGSNG	0.2289	0.2574	7.30E–04	6.39E–04	–10.69***	0.2427	0.2695	1.60E–03	3.59E–03	–5.25***

Note: * indicates significance at 0.1, ** indicates significance at 0.05, and *** indicates significance at 0.01.

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Table 5 shows the DCC-GARCH (E-GARCH) results. Table 6 shows the results obtained from the T-test performed on dynamic conditional correlation. The spillover from NIKKIE to ESTOXX 50 shows a significant persistence effect and a short-run effect. The contagion from NIKKIE to ESTOXX 50 and a significant negative asymmetric effect indicate that negative news exacerbates volatilities more than positive news. In the case of contagion from NIKKIE to ESTOXX 50, it is seen that both Θ_1 and Θ_2 are significant, thus showing that volatilities significantly affect the dynamic conditional correlations in the short and long terms. In the cases of contagion from ESTOXX 50 to NIKKIE, NIFTY 50 to FTSE 100, NIKKIE to ESTOXX 50, S&P 500 to HNGSNG, and S&P 500 to NIFTY 50, the asymmetric effect, short-run effect, persistence effect, and Θ_2 values are significant. Meanwhile, the volatilities impact the dynamic conditional correlations only in the long run. In the case of contagion from NIFTY 50 to NIKKIE, only the persistence effect is significant, while the asymmetric effect, short-run effect, Θ_1 and Θ_2 values are insignificant. This shows that in the case of contagion from NIFTY 50 to NIKKIE, the long-run and short-run impacts on the dynamic conditional correlations are independent of volatilities, which calls for a constant conditional correlation method.

4. DISCUSSIONS

This study finds that some cases of spillovers amongst the global stock markets are in congruence with Li (2021), Siriopoulos et al. (2021), Spulbar et al. (2022), Zeng and Lu (2022), and Nguyen (2023) demonstrating the time-varying and crisis sensitive nature of these spillovers. As per the DCC GARCH (S-GARCH) the contagion from ESTOXX to 50-FSTE 100, ESTOXX 50-FSTE 100, ESTOXX 50-NIKKIE, ESTOXX 50 to S&P 500, NIFTY 50 to FTSE 100, NIFTY 50 to NIKKIE, NIKKIE to ESTOXX 50, S&P 500-ASX 200, S&P 500-HNSGSNG, and S&P 500-NIFTY 50 show a significant difference after the invasion, thus these are the cases of contagion where the invasion had significant impact. DCC-GARCH (S-GARCH) shows the correlations between ESTOXX 50 and FTSE 100; ESTOXX 50 and NIFTY 50; NIFTY 50 and FTSE 100; NIFT 50 and NIKKIE; S&P 500 and NIFTY 50; S&P 500 and HNGNSNG are significantly higher after the declaration of the invasion (level of significance is less than five percent). On the other hand, correlations between ESTOXX 50 and S&P 500, NIKKIE and ESTOXX, and S&P 500 and ASX 200 show a significant decrease in correlation after the invasion (refer to Table 4).

Agreeing with Li (2021), Siriopoulos et al. (2021), Spulbar et al. (2022), Zeng and Lu (2022), and Nguyen (2023) that spillovers are crisis sensitive, the DCC-GARCH (E-GARCH) method finds the following pairs to have significant invasion-driven contagion after the declaration of invasion, from ESTOXX 50 to S&P 500, NIFTY 50 to FTSE, NIFTY 50 to NIKKIE, NIKKIE to ASX 200, NIKKIE to ESTOXX 50, NIKKIE to FTSE 100, S&P 500 to HNSNSG, and S&P 500 to NIFTY 50. Both DCC-GARCH (S-GARCH) and DCC-GARCH (E-GARCH) confirm invasion-triggered contagion for the following pairs: from ESTOXX 50 to S&P 500, NIFTY 50-FTSE100, NIFTY 50-NIKKIE, NIKKIE-ESTOXX 50, S&P 500-NIFTY 50, and SP500-HNGSNG. Figure 2 shows dynamic conditional correlations between significant spillovers. Again, in agreement with Li (2021), the downside spillovers are higher where the asymmetric effects happen to be significant. These asymmetric effects are the cases of contagion from ESTOXX 50 to NIKKIE, NIFTY 50 to FTSE 100, NIKKIE to ESTOXX 50, S&P 500 to HNGSNG, and S&P 500 to NIFTY 50 negative news is seen to have more impact on the volatilities than positive news. In disagreement with Li (2021), some of the spillovers have been found to be independent of the invasion. The transmission of volatilities from ESTOXX 50 to HNGSNG, FTSE 100-HNGSNG, HNGSNG-FTSE 100, HNGSNG-ESTOXX 50, NIKKIE to FTSE 100 and NIKKIE to ASX 200 were found to be independent of the invasion event using the DCC-GARCH (S-GARCH) method.

The DCC-GARCH (S-GARCH) shows that ESTOXX 50 is the highest source of invasion-driven contagion (four out of nine cases), in agreement with Umar et al. (2022). In the DCC-GARCH (E-GARCH) method, the invasion-

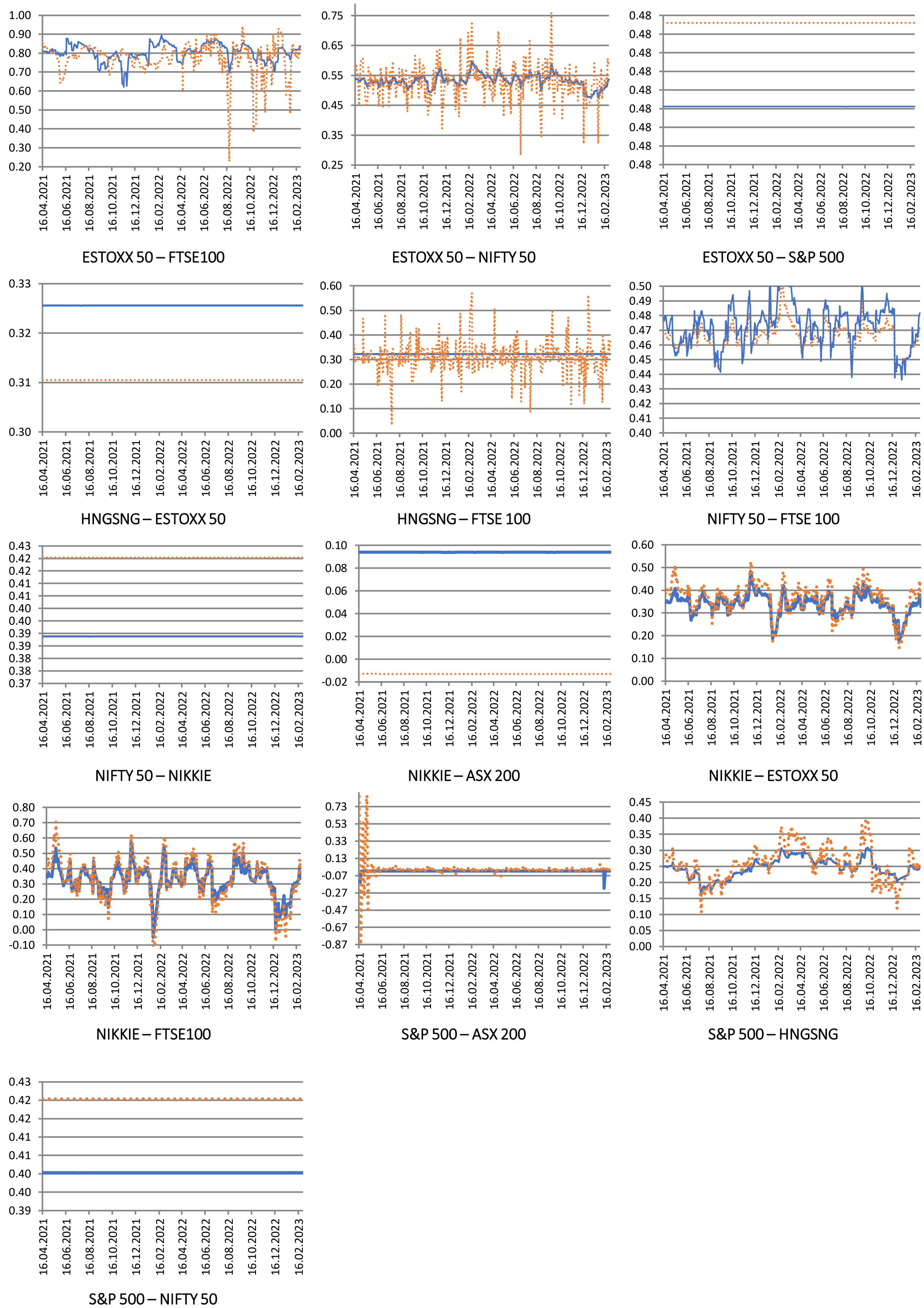

Figure 2. Dynamic conditional correlations for significant transmission

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triggered spillovers, NIKKIE was found to be the highest generator (three out of nine cases), while FTSE 100 and NIKKIE are the highest recipients (two cases each), differing from Umar et al. (2022). Interestingly, the DCC GARCH (E-GARCH) shows that, of the invasion-independent volatility transmissions, ESTOXX 50 is the highest generator (three out of seven cases), while FTSE 100 was the highest recipient with two cases. Moreover, the FTSE 100 is the highest recipient in invasion-driven and invasion-independent volatility transmissions. The DCCGARCH (E-GARCH) and the T-test on the dynamic correlations demonstrate that transmission of the volatilities from ESTOXX 50 to FTSE 100, ESTOXX 50 to HNGSNG, ESTOXX 50 to NIFTY 50, FTSE 100 to HNGSNG, HNGSNG to FTSE 100 and S&P 500 to ASX 200 are independent of the invasion event. Of these invasion-independent volatility transmissions, the transmission betwixt FTSE 100 and HNGSNG is mutually dependent.

Both DCC-GARCH (S-GARCH) and DCC-GARCH (E-GARCH) find the pair of S&P500 and ASX 200 to be negatively correlated, thus forming a natural hedge before and after the invasion. The DCC-GARCH (E-GARCH) finds that NIKKIE and ASX 200 demonstrate a negative correlation before and after the invasion, indicating a natural hedge in the pair, as per Zeng and Lu (2022), who recommend that negatively correlated pairs form a natural hedge. The study also finds that DCC-GARCH (E-GARCH) provides superior accuracy in comparison to DCC-GARCH (S-GARCH), which is in congruence with Singhal and Ghosh (2016).

Daily data on respective stock market indices were collected from Yahoo! Finance for 2023. Links are provided below.

ESTX 50 PR.EUR (^STOXX50E) – https://finance.yahoo.com/quote/%5ESTOXX50E/history/

FTSE 100 (UKX.L) – https://uk.finance.yahoo.com/quote/ukx.l/history/

HANG SENG INDEX (^HSI) – https://finance.yahoo.com/quote/%5EHSI/history/

NIFTY 50 (^NSEI) – https://finance.yahoo.com/quote/%5ENSEI/history/

Nikkei 225 (^N225) – https://finance.yahoo.com/quote/%5EN225/history/

S&P 500 (^GSPC) – https://finance.yahoo.com/quote/%5EGSPC/history/

S&P/ASX 200 (^AXJO) – https://au.finance.yahoo.com/quote/%5EAXJO/history/

CONCLUSION

The study finds whether Russia's invasion of Ukraine impacted the spillovers amongst the global stock markets. The DCC-GARCH and the T-test employed show that the invasion significantly impacted the contagion amongst the global stock markets. In fact, the study shows a significant increase in the correlation coefficient after the declaration of the invasion in most cases. Moreover, the study finds ESTOXX 50 as the greatest source of invasion-driven contagion owing to the stock exchange's geographical proximity to the war zone. The study also observes that FTSE 100 is the highest recipient of invasion-driven spillovers, indicating that FTSE 100 constituents are the most vulnerable to this Russian invasion of Ukraine.

As for predictive accuracy, the study reiterates the superiority of DCC-GARCH (E-GARCH) over DCC-GARCH (S-GARCH), as per the AIC (Akaike Information Criterion). The study suggests ASX 200 and S and P 500 as a natural hedge pair for global investors during the invasion period.

The work lays down a premise for further investigation on channels for war-driven spillovers like geographical proximity, trade linkages, migratory patterns, capital flows, etc.

AUTHOR CONTRIBUTIONS

Conceptualization: Satya Krishna Sharma Raavinuthala, Girish Jain.
Data curation: Satya Krishna Sharma Raavinuthala, Gokulananda Patel.
Formal analysis: Satya Krishna Sharma Raavinuthala, Girish Jain.
Methodology: Satya Krishna Sharma Raavinuthala, Gokulananda Patel.
Supervision: Gokulananda Patel.
Validation: Girish Jain, Gokulananda Patel.
Writing – original draft: Satya Krishna Sharma Raavinuthala.
Writing – review & editing: Girish Jain, Gokulananda Patel.

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