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Liu, Xiaoxing; Shehzad, Khurram

#### Article

Analyzing time-different connectedness among systemic financial markets during the financial crisis and conventional era: New evidence from the VARX-DCC-MEGARCH model

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## Analyzing time-different connectedness among systemic financial markets during the financial crisis and conventional era: New evidence from the VARX-DCC-MEGARCH model

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### Analyzing time-different connectedness among systemic financial markets during the financial crisis and conventional era: New evidence from the VARX-DCC-MEGARCH model

Xiaoxing Liu and Khurram Shehzad

School of Economics and Management, Southeast University, Nanjing, China

#### ABSTRACT

This investigation utilized the VARX-DCC-MEGARCH model assimilated with skewed-t density to analyze the time-different (i.e., daytime, overnight, and daily) connectedness among S&P 500, DAX 30, FTSE-100, Nikkei 225, and Shanghai Composite Index. This investigation discovered that the current davtime returns transmission from the DAX 30, FTSE 100, and Nikkei 225 index to ensuing overnight returns of the S&P 500 index was inconsequential during the stable period. The study also quantified that shocks befallen in the current overnight returns of the S&P 500 partake bidirectional and negative ties with shocks that occurred in subsequent day-wise returns of the DAX 30 index. Moreover, during crises, only the Shanghai composite index spillovers the volatility of the FTSE 100 index. The study revealed a leverage effect for the day-wise return of the S&P 500, DAX 30, and overnight returns of the FTSE 100 index.

#### **ARTICLE HISTORY**

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#### **KEYWORDS**

Returns transmission; Volatility spillover effect; Time-varying correlations; Leverage effect; Financial crisis

#### 1. Introduction

The mounting trend of globalization and liberalization has transformed whole nations into one economy, instigating the integration of financial markets among the nations (Shehzad, Liu, et al., 2021). Besides, Information and Communication Technology (ICT) has played a vital role in connecting people worldwide. Notably, digital apps like bloom berg, yahoo finance, Merril Edge, Charles Schwab, and TD Ameritrade offer opportunities to financiers of any nation to register and buy stocks online at any time in the world (Rosenberg, 2020). So, on account of advanced ICT and globalization, a piece of economic news, political news, industry-specific news, or any other good or abysmal news related to financial markets occurring in any part of the globe would directly impinge on the prices of financial assets at the national level and worldwide (Bala & Takimoto, 2017). Consequently, high vacillations in the asset returns may intensify the financial risk, leading to financial calamities in the markets. In a similar vein, the history of financial markets demonstrates that economic crises,

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CONTACT Khurram Shehzad 🖾 khurramscholar64@hotmail.com; 233189917@seu.edu.cn 📼 School of Economics and Management, Southeast University, Building 9, Juyuan, Jiulonghu Campus, Nanjing, China

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such as sovereign debt crises (1982), stock market crashes (1987), Mexican crises (1994), Asian crises (1997–1998), Russian debt crises (1998), Greek debt crises (2009), and global financial crises (GFC) (2007–2009), had a significant impact on the stability of the global financial system (Shehzad et al., 2020). Jonathan Law (2008) argued that systemic risk was the vital motive of GFC. Thus, the study regarding the assimilation of financial markets and the reckoning of financial risk has grown into an indispensable subject and seized the attention of policymakers, academicians, and finance managers (Shehzad, Bilgili, et al., 2021).

Numerous studies (Berkowitz & O'Brien, 2002; McNeil & Frey, 2000; MKP & PLH, 2006) employed univariate GARCH models to discover the volatilities. Given that, to deal with multiple asset returns in a portfolio, a multivariate version of the GARCH model is suitable to evaluate the volatility pattern. Likewise, several multivariate GARCH models have been instituted to quantify the conditional variance and covariance of financial assets, i.e., GO-GARCH, BEKK-GARCH, and CCC-GARCH models (for more detail on MGARCH models, see (Ghalanos, 2015; Silvennoinen & Teräsvirta, 2009). This investigation utilized the Dynamic Conditional Correlation (DCC) Multivariate Exponential Generalized Autoregressive Conditional Heteroskedasticity (MEGARCH) model (Nelson, 1991; R. Engle, 2002), merged with a robust version of the Vector Autoregressive with exogenous instruments (VARX) model. The DCC model cogitates the time-varying correlation between the factors and can manage the vast extent of matrices (Ahmad et al., 2013). Besides, the MEGARCH model can figure out the asymmetric effect (Shehzad, Liu, et al., 2021). Furthermore, a good volatility model not only considers the nature of tail distribution appropriately but can also handle many assets (Malz, 2011). Countless studies have been conducted to define the transmission of the returns and shock spillover among developed, emerging, and under-developing nations (e.g., Ali & Afzal, 2012; BenSaïda et al., 2018a; Jebran & Iqbal, 2016; Li, 2007; Sikhosana & Aye, 2018). However, prior studies do not ponder the time difference to determine the transmission of returns, shock spillover, and portfolio VaR among the financial markets. The actual examination used data from the FTSE 100, S&P 500, Nikkei 225, DAX 30, and Shanghai Composite index (SSEC) to determine the nominations for the United Kingdom, United States, Japan, Germany, and Chinese stock markets, respectively. Figure 1 exhibits the time dissimilarity of each nation with other nations. According to Greenwich Mean Time (GMT), the financial sun arises from London (UK), which is 5 h ahead of the US. Though Japan, China, and Germany are 14 h, 13 h, and 6 h ahead of the US, respectively. The plots displayed that Japan is 1 h ahead of China, 8 h ahead of Germany, and 9 h ahead of London. In comparison, China unveiled 7 h difference from Germany and 8 h from London. In the end, Germany designates a 1 h difference from London. Thus, the stockholders of one's market are aware of the returns of other markets. Given the time difference between the closing of one market and the opening of another market may provide profitable trading occasions. This phenomenon presents the importance of choosing these stock markets. Moreover, these markets are known as the most developed markets and substantiate a considerable portion of the world's financial market capitalization (Bayoumi & Bui, 2012). Also, Belke and Dubova (2017) referred to the equity and bond markets of the US, Europe, the UK, and Japan as systemic financial markets. Furthermore,



Figure 1. Time Transformation graph.

these stock markets also have prominence because the currency of these countries is listed in the Currency Basket.<sup>1</sup> of International Monetary Fund (International Monetary Fund, 2016), and acute fluxes befallen in these markets can harm the world's economy. Consequently, it turns essential to understand the financial risk pattern of these markets during and after the GFC era. So, effective policies can be generated, and any financial calamities in the future can be managed efficiently and timely.

The critical contribution of this investigation is to scrutinize the time-different pattern of returns and volatility linkages among DAX 30, S&P 500, Nikkei 225, SSEC, and FTSE 100 index so that it can be determined which markets are significant transmitters and receivers of risk, and whose returns have a bidirectional, unidirectional, positive, and negative association with other markets. Combining these markets should bring superfluous understandings into financial management research. This research also recognized the summary and plots of time-varying correlation among these markets. Besides, it enlightened the role of global oil prices for return changes in these stock markets. The general research questions of this investigation are as follows. First, does the return transmission of these equity markets show any directional configuration, and can timedifferent return transmission offer profitable opportunities? Second, what is the nature of time-different shock spillovers among these markets? Third, how differently do return transmission and shock spillover behave during financial crises compared to stable periods? Fourth, is financial risk diversification possible within these equity markets? Fifth, does the time-varying correlation of a stable period differ from GFC? Finally, what

<sup>&</sup>lt;sup>1</sup>A currency basket contains different currencies with specific weights. These currencies are used to determine the market value of other currencies. The currency basket of IMF includes five currencies, i.e., the US dollar, Japanese Yen, Euro, Chinese RMB, and British Pound.

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insinuations can be derived from this analysis, especially to understand the financial risk pattern of these stocks? After answering these questions, we aim to extend our knowledge about these markets' time-different financial risk patterns.

According to the author's best knowledge, no existing investigation has employed this strategy to evaluate these markets' returns transmission, volatility spillovers, and portfolio VaR. The analysis of this study will offer essential policy suggestions for investors, policy builders, finance managers, and portfolio managers. The rest of this article is structured as follows. Section 2 confers the enhanced literature review, section 3 refers to the superior and comprehensive data and methodology of this investigation, section 5 gives an interpretation and detailed discussion of results, and section 6 expresses the conclusion, policy implications, and future recommendations. Finally, the references used in this study are given in section 6.

#### 2. Literature review

One of the critical concerns in financial markets is the notion of financial risk due to information spillovers. Numerous essential studies related to the financial market's risk and their dependence on each other have been reviewed in this study. For example, Aumeboonsuke (2019) identified that co-movements among equity markets upsurge financial instability. The outcomes of the vector error correction model recommend that returns of US and UK stock markets have some degree of sway on ASEAN markets. However, investment in ASEAN markets provides a healthier mean-variance portfolio. The study of Natarajan et al. (2014) stated that mean returns of the US meaningfully transfer to Australia and Germany. The analysis also found high volatility persistence for these markets. Furthermore, Jawadi et al. (2015) found weak evidence of volatility transmission between European and US markets, while through the post crises period, the inspection recorded bidirectional volatility spillover and returns transmission impact between US and European equity markets. Yoon et al. (2019) stated that the US is a major contributor to the transmission of returns, and financial crises intensify the spillover effects among financial markets. Y. Wang et al. (2018) argued that GARCH models present poor out-of-sample forecast results. The study used an in-sample strategy to gauge the stock markets of Canada, Japan, Germany, the US, and the UK and revealed noteworthy volatility spillover evidence from the US to other nations. Additionally, Belke and Dubova (2017) analyzed volatility transmission among equity and bond markets of the US, Europe, the UK, and Japan. The investigation indicated that these nations' equity and bond markets highly accompany each other. Further, Sarwar et al. (2019) exploited daily data from SSEC, the Nikkei index, the Bombay stock exchange, and the oil market. The investigation publicized that oil returns and Nikkei index returns have a bidirectional spillover relationship. The study suggested that investors should choose more equity markets than oil assets to gain more profit.

Indeed, BenSaïda et al. (2018b) examined volatility spillover impact across financial markets for GFC and tranquillity. The examination discovered that during the GFC, directional volatility spillovers grow into highly intensive and vary among net risk transmission and net risk receivers, while during the standard period, it showed a moderate impact. Moreover, Lien et al. (2018) questioned the shock spillovers among East Asian and US equity markets during the period of US subprime credit crises and

Asian currency crises. The consequences revealed a unidirectional shock spillover effect from the US to East Asian markets during both periods. However, Yarovaya et al. (2016) Stated that financial markets are highly vulnerable to local and region-specific volatility. Likewise, Smolović et al. (2017) evaluated different GARCH models using the daily returns of the Montenegrin stock market index. The study made known that ARMA (1, 2)-TS-GARCH (1, 1), ARMA (1, 2)-T-GARCH (1, 1), and ARMA (1, 2)-EGARCH (1, 1) combined with student-t distribution and Johansen distribution has accepted the Christoffersen test at 95% confidence level. Additionally, Louzis et al. (2011) utilized the fully parametric approach and mentioned that GARCH and realized volatility models united through filtered historical simulation and extreme value theory methods guesstimate superior VaR during the GFC. The study also stated that skewed student distribution is a good alternative when high market fluctuations.

This recent literature review exposed that, according to many studies, shocks significantly impact the stability of other markets. It designates the importance of unveiling the world's largest stock markets' behavior. Moreover, the literature showed that no investigation had considered the time difference among the US, Japan, China, Germany, and the UK stock markets to capture returns transmission and volatility spillover effects. Additionally, we could not find a study that employed the VARX-DCC-GARCH model combined with skewed-t density to evaluate the volatilities. Therefore, to fill the gap, this research ponders the difference between these stock markets' opening and closing times and evaluates the returns transmission and volatility spillover during and after the GFC period.

#### 3. Data and methodology

#### 3.1. Data

This study has employed daily data from five stock markets of reformist economies, e.g., S&P 500 (US), Nikkei 225 (JAPAN), DAX 30 (Germany), SSEC (China), and FTSE 100 (UK). This investigation has utilized the data from 2007 to 2019 and divided it into two panels, i.e., panel A from 4 January 2010 to 27 November 2019, which epitomizes the regular period, and panel B from 4 January 2007 to 31 December 2009, which represents the GFC. The study also includes the impact of crude oil prices as an exogenous factor, and all the data is occupied from the database of yahoo finance and US Energy Information and Administration.

#### 4. Methodology

The examination has premeditated the daily returns by following the methodology of Bhuyan et al. (2016) as follows,

$$R_{t} = (In(CS_{t}/CS_{t-1})) * 100$$
(1)

Moreover, this examination has alienated daily returns into overnight returns and daywise returns as follows,

$$\mathsf{DR}_{\mathsf{t}} = (\mathsf{In}(\mathsf{CS}_{\mathsf{t}}/\mathsf{OS}_{\mathsf{t}})) * 100 \tag{2}$$

$$NR_{t} = (In(OS_{t}/CS_{t-1})) * 100$$
(3)

here, R<sub>t</sub>, DR<sub>t</sub> and NR<sub>t</sub> denote daily, day-wise, and overnight returns, respectively. Moreover,  $CS_t$ ,  $CS_{t-1}$ , and  $OS_t$  symbolize the closing price of a stock on day t, day t-1, and the opening stock price on day t, respectively. Hence, the labels of overnight returns (NR) and daytime returns (DR) can be abbreviated as; SPNR (S&P 500), SPDR (S&P 500), DAXNR (DAX30), DAXDR (DAX30), LSENR (FTSE 100), LSEDR (FTSE 100), SSENR (SSEC), SSEDR (SSEC), NKNR (Nikkei 225) and NKDR (Nikkei 225). In order to internment vibrant possible evidence of returns transmission and risk spillover, this investigation has applied a newly designed econometric model. Indeed, this investigation employed the Dynamic Conditional (DCC) Multivariate Exponential Generalized Autoregressive Correlation Conditional Heteroskedasticity (MEGARCH) model (Nelson, 1991; R. Engle, 2002) with the combination of a robust version of Vector Autoregressive incorporated with exogenous variable (VARX) model (Croux & Joossens, 2008). The VARX-DCC-MEGARCH model has plentiful qualities as compared to standard GARCH models. The GARCH model only ruminates the magnitude of stock returns to compute future volatility, and an increase or decrease in stock returns is ignored. Whereas the MEGARCH model assumes a parametric approach for conditional heteroskedasticity. Moreover, the GARCH model placed some constraints on parameters despoiled by estimated coefficients and confines the procedure of conditional variance. Also, in the GARHC model, it is hard to ensure that shocks to conditional volatility persist or not (Nelson, 1991). However, the MEGARCH model can handle asymmetric volatility shocks as it does not impose non-negativity constraints on parameters (Shehzad, Liu, et al., 2021). Financial risk analysis and asset allocation mainly rely on correlations among financial assets, requiring many correlation series (BenSaïda et al., 2018a). Further, building an optimal portfolio with maximum return and minimum variance needs forecasting of the covariance matrix of asset returns, and it is also needed to determine the standard deviation of a portfolio. The DCC GARCH model estimates the covariance matrix and conditional correlation directly. Moreover, the number of factors to be evaluated in the correlation procedure is not dependent on the number of series. Consequently, calculating the copious quantity of correlation matrices becomes possible (R. Engle, 2002).

#### 4.1. Weighing up of the VARX model

This investigation employed a robust version of the VAR model by utilizing the Multivariate Least Trimmed Square (MLTS) estimator. Hence, by way of (Croux & Joossens, 2008), we postulate VARs with one lag for both periods as (Liu et al., 2022);

$$r_{i,t} = w_{i,0} + \sum_{i=0}^{n} w_{i,j} r_{j,t-1} + v_{i,t},$$
for  $i = 1, \dots, n,$  (4)

Here, in the mean model Eq. (4),  $r_{i,t}$  denotes assets return series *i* at time t, and  $w_{i,0}$  nominates the constant term of series *i* at time t. However, when  $i \neq 0$  then  $w_{i,j}$  nominates the coefficient that quantifies the transmission impact of financial asset return series *j* to *i*. However, when i = j, it calculates the lagged impact of its own returns on the succeeding value. Furthermore,  $v_{i,t}$  indicates the error term of series *i* at time t, and *n* represents the number of variables included in the study, i.e., n = 10.

#### 4.2. DCC-MEGARCH model

$$\sigma_{i,t}^{2} = \exp\left\{\mu_{i} + \sum_{i=0}^{n} n_{i,j} \left(\frac{|v_{j,t-1}|}{\sqrt{\sigma_{j,t-1}^{2}}} + \partial_{j} \frac{v_{j,t-1}}{\sqrt{\sigma_{j,t-1}^{2}}}\right) + \delta_{i} \ln\left(\sigma_{i,t-1}^{2}\right)\right\}, \text{ for } i = 1, \dots, n.$$
(5)

Similarly, in the variance equation Eq. (5),  $\sigma_{i,t}^2$  signifies the conditional variance of series *i* at time t. Additionally,  $\mu_i$  symbolizes the constant term of variance series *i*, and when  $i \neq j$ ,  $n_{i,j}$  is the factor that delineates risk transmission impact from financial asset series *j* to *i*. Nonetheless, when i = j,  $n_{i,j}$  represents the ARCH coefficient that reckons the impact of shocks in returns on its own variance series *i* at time t+1. Moreover,  $\delta_i$  and  $\partial_j$  determine the impact of changes in the volatility of its own variance series *i* at time t+1, i.e., GARCH effect, and asymmetry impact of return series *j*, i.e., leverage effect, respectively. Moreover, DCC incorporated with a skewed-t density model delivers enriched findings (Bala & Takimoto, 2017). By following (Bauwens & Laurent, 2005), this study considers the multivariate skewed-t student distribution as follows,

$$f(\boldsymbol{Y}_t|\boldsymbol{\nu},\boldsymbol{\psi}) = \left(\frac{2}{\sqrt{\pi}}\right)^n \left(\prod_{i=1}^n \frac{\boldsymbol{\nu}_i S_i}{1+\boldsymbol{\nu}_i^2}\right) \frac{\Gamma(\frac{\boldsymbol{\psi}+n}{2})}{\Gamma(\frac{\boldsymbol{\psi}}{2})[\pi(\boldsymbol{\psi}-2)^{n/2}} \left[1+\frac{Y'Y}{\boldsymbol{\psi}-2}\right]^{-n+\boldsymbol{\psi}/2}$$
(6)

where 
$$Y_t = (Y_{1,t} \dots Y_{n,t}),$$
 (7)

$$Y_{i,t} = (s_i z_i + m_i) \boldsymbol{\nu}_i^{Ii}, \tag{8}$$

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$$m_i = \frac{\Gamma(\frac{\psi-1}{2})\sqrt{\psi-2}}{\sqrt{\pi}\Gamma(\frac{\psi}{2})} (\boldsymbol{v}_i - 1/\boldsymbol{v}_i), \tag{9}$$

$$s_i^2 = \left(\mathbf{v}_i^2 + \frac{1}{\mathbf{v}_i^2} - 1\right) - m_i^2,$$
(10)

and 
$$I_i = \begin{cases} -1 & \text{if } z_i \ge -m_i/s_i \\ 1 & \text{if } z_i < -m_i/s_i \end{cases}$$
(11)

here in Eq. (6)-(11),  $m_i$  and  $s_i^2$  are not the further factors, but these are functions of  $vand\psi$ , and v symbolizes the asymmetric/skewness parameter vector of series i. While  $\psi$  and n denote the degree of freedom and number of variables involved in the model, respectively. Moreover,  $s_i$  stands for standard deviation, and  $m_i$  is the mean value of series i. Besides, when  $\ln v_i > 0$ , it is called right skewness, but when  $\ln v_i < 0$ , it nominates the left skewness of the distribution of series i (Bauwens & Laurent, 2005). This study follows the methodology of (R. Engle, 2002) to model the DCC as follows,

$$H_t = \Im_t \Re_t \Im_t \tag{12}$$

where  $H_t$  denotes the  $k \times k$  covariance matrix and conditional volatility, and  $\Re_t$  stands for the conditional correlation matrix among the financial return series. Whereas  $\Im_t$ designates the diagonal standard deviation matrix.

here, 
$$\Im_t = diag(\xi_{1,t,\dots},\xi_{n,t}),$$
 (13)

and 
$$\mathcal{R}_t = diag\left(\frac{1}{\sqrt{\varsigma_{1,1,t_i}}}, \dots, \frac{1}{\sqrt{\varsigma_{n,n,t_i}}}\right) t diag\left(\frac{1}{\sqrt{\varsigma_{1,1,t_i}}}, \dots, \frac{1}{\sqrt{\varsigma_{n,n,t_i}}}\right)$$
 (14)

where  $\varphi_t$  is a symmetric positive definite matrix;

$$_{t} = \begin{bmatrix} \boldsymbol{\varsigma}_{1,1,t,} & \cdots & \boldsymbol{\varsigma}_{1,n,t,} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\varsigma}_{n,1,t,} & \cdots & \boldsymbol{\varsigma}_{n,n,t,} \end{bmatrix}$$
(15)

 $\phi_t$  Can also be outlined as;

$$t_{t} = (1 - \omega - \vartheta)^{-} + dz_{t-1}z_{t-1} + q_{t-1},$$
 (16)

Panel A.	SPNR	SPDR	DAXNR	DAXDR	LSENR	LSEDR	SSENR	SSEDR	NKNR	NKDR	OIL
Mean	0.016	0.021	0.041	-0.010	0.041	0.057	-0.106	0.106	0.043	-0.010	4.2365
Std. Dev.	0.222	0.871	0.658	1.000	0.879	1.456	0.585	1.2190	0.8039	0.9244	0.3219
Skewness	-0.386	-0.642	-2.058	-0.2308	-3.510	0.5265	-1.409	-0.288	-0.125	-1.417	0.8926
Kurtosis	8.604	5.434	32.73	3.6412	68.382	5.7488	37.590	5.0394	-0.026	14.530	3.853
Jarque-B	6642	2775	96868	1199	420560	3040.2	126470	2289	5.6899	19505	133
P-values	0	0	0	0	0	0	0	0	0	0	0
ADF Stat.	48.1	-48.90	-38.096	-45.486	-35.83	-46.061	-9.1449	-47.453	-47.12	-51.50	-49.40
P-values	0	0	0	0	0	0	0	0	0	0	0
Arch(10)(χ2)	340.91	542.49	14.838	256.47	2.1998	60.21	363.63	331.94	177.42	88.03	2114.3
P-values	0	0	0	0	0	0	0	0	0	0	0
Ljung-Box	32.868	68.368	59.454	38.077	27.347	16.22	172	34.161	36.149	61.316	40907
(20) Divelues	•	0	0	0	0	0	0	0	•	^	0
P-values											0
Panel B.	SPINK	SPUR				LSEDK	55EINK	55EDK			01L
Mean Ctal David	-0.020	-0.045	-0.018	-0.0328	-0.305	0.2125	-0.1093	0.107	-0.006	-0.064	4.311
Sta. Dev.	0.225	1./541	0.740	1.5523	1./415	3.2857	1.110/	2.16/	0.8053	1.6596	0.324
Skewness	-0.778	-0.351	-3.024	0.2735	-1.853	0.5197	1.3809	-0.3615	-0.105	-0.312	0.665
Kurtosis	5.199	5.494	29.62	6.240	13.624	3.1526	15.6/9	1.286	-0.866	10.99	7.53
Jarque-B	807.83	841.2	25059	10/5.9	5466.2	302.12	6949.3	59./13	21.814	3325.3	50.2
P-values	0	0	0	0	0	0	0	0	0	0	0
ADF Stat.	-31.46	-30.03	-29.33	-23.33	-4.938	-15.32	-14.31	-29.405	-26.84	-27.82	-26.9
P-values	0	0	0	0	0	0	0	0	0	0	0
Arch(10)(χ2)	99.13	181.17	91.132	160.66	115.59	76.767	96.17	19.693	97.388	274.5	640.4
P-values	0	0	0	0	0	0	0	0.032	0	0	0
Ljung-Box(20)	116.8	49.13	72.765	58.865	259.46	39.343	51.956	46.373	23.345	41.779	12021
P-values	0	0	0	0	0	0	0	0	0.2722	0	0

Table 1. Descriptive statistics, ADF, and ARCH test.

Source: Author's Calculation.

where  $\overline{\phi}$  is the  $k \times k$  correlation matrix of standardized residuals, and  $z_t$  is the  $k \times 1$  vector of standardized residuals. Further, the DCC factors  $\omega$  and  $\vartheta$  are supposed to have positive values whose sum does not increase from unity. Hence, the time-varying DCC matrix can be computed as follows;

$$\mathsf{C}_{ij,t} = \frac{\varsigma_{i,j,t,}}{\sqrt{\varsigma_{i,i,t}\varsigma_{j,j,t}}} \tag{17}$$

#### 5. Results and discussions

Table 1 belongs to the descriptive statistics for both categories evaluated in this investigation. The outcomes showed that in the course of GFC, most indices showed negative mean returns except LSEDR and SSEDR, with high standard deviation values. The study showed that skewness values of all the variables are negative except LSEDR and OIL, while during the GFC period, DAXDR, LSEDR, SSENR, and OIL showed positive skewness. Further, the kurtosis values of all the variables for both categories are more than usual, which implies that there are high chances of tremendous earnings or loss (Shehzad, Xiaoxing, et al., 2021). This investigation applied the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979), and found that all the indices are stationary at the level for both sets. Moreover, the examination employed ARCH LM (R. F. Engle, 1982) test, and the Ljung-Box test, and discovered that variables have a strong ARCH effect and serial correlation for



Figure 2. Returns distribution and oil prices.

both ages, respectively. Also, Figure 2 provides evidence of volatility clustering in the data. Consequently, the GARCH model is impeccably appropriate for this analysis (Sobti, 2018).

	Coefficient	P-Values		Coefficient	P-Values		Coefficient	P-Values
Mean eo	quation of SPNF	R (1)	w4,5	0.009693	0.604	w7,10	-0.010144	0.151
w1,1	_0.0318*	0.0614	w4,6	0.007671	0.150	w7,11	-0.012798	0.435
w1,2	-0.0041	0.2744	w4,7	0.057688*	0.091	ć	-0.03461***	0.000
w1,3	0.00569	0.5051	w4,8	-0.01086	0.423	Mear	n equation of SSE	EDR (8)
w1,4	-0.0053	0.2473	w4,9	-0.02666	0.242		Coefficient	P-values
w1,5	-0.0096	0.1014	w4,10	-0.00125	0.763	w8,1	-0.41365***	0.000
w1.6	-0.001	0.9712	w4.11	0.066511	0.410	w8.2	0.012988	0.550
w1.7	0.00335	0.6640	ć	-0.27683	0.489	w8.3	-0.021669	0.668
w1,8	-0.0066**	0.0291	Mea	n equation of LS	ENR (5)	w8,4	0.0280861	0.275
w1,9	0.0011	0.8762		Coefficient	P-values	w8,5	-0.005399	0.821
w1,10	-0.0025	0.5399	w5,1	0.002858	0.9327	w8,6	0.0075773	0.870
w1,11	-0.0212**	0.0146	w5,2	0.300764***	0.0000	w8,7	-0.22179***	0.000
Ċ	0.11439***	0.0000	w5,3	-0.09528***	0.0000	w8,8	0.0064371	0.673
Mean eo	quation of SPDF	R (2)	w5,4	-0.13911***	0.0000	w8,9	0.0335866	0.232
	Coefficient	P-Values	w5,5	-0.00662	0.7648	w8,10	0.0117026	0.580
w2,1	0.0539	0.504	w5,6	-0.00486	0.5992	w8,11	-0.21465***	0.002
w2,2	-0.0232	0.170	w5,7	0.003353	0.1118	ć	1.026513***	0.000
w2,3	-0.0153	0.751	w5,8	-0.00662**	0.0166	Mea	n equation of NK	NR (9)
w2,4	-0.0088	0.782	w5,9	0.001105	0.6445		Coefficient	P-Values
w2,5	0.03968*	0.057	w5,10	-0.00255**	0.0280	w9,1	0.245763***	0.0000
w2,6	0.02836**	0.018	w5,11	-0.02123**	0.0124	w9,2	0.557954***	0.0000
w2,7	0.00746	0.722	Ċ	0.114385***	0.0003	w9,3	-0.040562*	0.0781
w2,8	0.00808	0.524	Mea	in equation of LSI	EDR (6)	w9,4	0.196691***	0.0000
w2,9	0.00155	0.906		Coefficient	P-values	w9,5	0.0054738	0.6958
w2,10	-0.0395**	0.017	w6,1	-0.20283	0.110	w9,6	0.0117522**	0.0576
w2,11	0.11372**	0.015	w6,2	0.216102***	0.000	w9,7	-0.011106	0.5584
С	-0.4392	0.138	w6,3	0.057706	0.416	w9,8	-0.009729	0.2631
Mean eo	quation of DAX	NR (3)	w6,4	-0.01541	0.445	w9,9	-0.001384	0.9699
	Coefficient	P-Values	w6,5	-0.06436	0.131	w9,10	-0.10904***	0.0000
w3,1	0.07587	0.101	w6,6	0.024369**	0.026	w9,11	0.0180308	0.9030
w3,2	0.34103***	0.000	w6,7	0.000401	0.994	С	-0.05755	0.6876
w3,3	-0.071***	0.000	w6,8	0.023807	0.339	Mear	n equation of NK	DR(10)
w3,4	-0.158***	0.000	w6,9	-0.02591	0.460		Coefficient	P-Values
w3,5	-0.0238*	0.081	w6,10	0.00818	0.963	w10,1	-0.201224**	0.010
w3,6	-0.0033	0.746	w6,11	0.199392*	0.051	w10,2	-0.013062	0.682
w3,7	-0.0395**	0.017	С	-0.80966	0.141	w10,3	-0.004953	0.731
w3,8	-0.0224	0.004	Mea	in equation of SSI	ENR (7)	w10,4	0.123035***	0.000
w3,9	-0.0025	0.966		Coefficient	P-values	w10,5	-0.043491*	0.056
w3,10	-0.0482***	0.000	w7,1	0.264905***	0.000	w10,6	0.0029479	0.873
w3,11	-0.0292	0.318	w7,2	0.187154***	0.000	w10,7	0.002663	0.950
С	0.17672***	0.008	w7,3	0.005337	0.775	w10,8	-0.012993	0.346
Mean eo	quation of DAX	DR (4)	w7,4	0.049664***	0.000	w10,9	0.0344144*	0.070
	Coefficient	P-Values	w,7,5	-0.00291	0.799	w10,10	-0.047818**	0.025
w4,1	-0.1976**	0.026	w7,6	-0.00239	0.636	w10,11	0.0056077	0.783
w4,2	0.03056	0.451	w7,7	0.003297	0.700	С	0.0212929	0.545
w4,3	0.01481	0.740	w7,8	0.03092***	0.000			
w4,4	0.03707	0.183	w7,9	-0.01922**	0.014			

Table 2. Results of the VARX model (panel A).

\*, \*\*, \*\*\* denotes 10%, 5%, and 1% level of significance.

Here, number 11 denotes the exogenous variable of the global OIL prices series.

Source: Author's calculation.

#### 5.1. Return Transmission Repercussions (VARX)

Table 2 outlines that SSEDR and DAXDR have bivariate liaisons with SPNR and SSENR, respectively. Also, SPDR (w5, 2) and NKDR (w5, 10) indicated bivariate bonding with LSENR. While LSEDR (w2, 6) ominously shakes the SPDR and vice versa. Further, NKDR (w2, 10) adversely impacts SPDR, while DAXDR (w3, 4), SSENR (w3, 7), and SSEDR (w3, 8) have a negative influence on DAXNR.

Table 3.	Results (	of the	VARX	model	(panel	B).
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	Coefficient	P-values		Coefficient	P-values		Coefficient	P-values
Mean eq	uation of SPNR	(1)	w4,5	0.01394	0.67321	w7,10	-0.02647	0.12213
w1,1	-0.1608***	0.00000	w4,6	0.05142***	0.00114	w7,11	-0.19485***	0.00000
w1,2	-0.01201**	0.00313	w4,7	0.02158	0.63643	С	0.75761**	0.01171
w1,3	0.03441***	0.00000	w4,8	0.00194	0.92773	Mear	n equation of SSE	DR (8)
w1,4	-0.00909*	0.07272	w4,9	0.03217	0.64330		Coefficient	P-values
w1,5	-0.00480	0.23817	w4,10	0.03751	0.27498	w8,1	-0.17787	0.67631
w1,6	0.00357*	0.06621	w4,11	-0.08849	0.52476	w8,2	0.03780	0.51062
w1,7	-0.00916	0.10280	С	0.37863	0.53019	w8,3	-0.30978**	0.02837
w1,8	-0.00008	0.97629	Mea	n equation of LS	ENR (5)	w8,4	-0.02356	0.74215
w1,9	-0.00048	0.95541		Coefficient	P-values	w8,5	0.00794	0.89008
w1,10	-0.00672	0.11175	w5,1	-0.32494*	0.06072	w8,6	-0.01763	0.52101
w1,11	-0.00754	0.65939	w5,2	0.48237***	0.00000	w8,7	-0.09459	0.23357
С	0.02595	0.72654	w5,3	-0.23015***	0.00000	w8,8	-0.14005***	0.00000
Mean eq	uation of SPDR	(2)	w5,4	-0.23554***	0.00000	w8,9	0.22185*	0.06635
	Coefficient	P-Values	w5,5	0.07857***	0.00000	w8,10	-0.17458***	0.00348
w2,1	0.52010**	0.03510	w5,6	-0.02274**	0.04183	w8,11	-0.63180***	0.00900
w2,2	-0.22187***	0.00000	w5,7	-0.06677**	0.03866	C	2.90420***	0.00500
w2,3	-0.17652**	0.03108	w5,8	0.01022	0.49965	Mea	n equation of NK	NR (9)
w2,4	0.04227	0.30817	w5,9	-0.02579	0.59964		Coefficient	P-values
w2,5	-0.02729	0.41238	w5,10	-0.06075**	0.01241	w9,1	0.15878*	0.08974
w2,6	0.00974	0.54074	w5,11	0.11106	0.22533	w9,2	0.39262***	0.00000
w2,7	0.03047	0.50766	Ċ	-0.51722	0.25904	w9,3	0.17088***	0.00000
w2,8	0.00096	0.96432	Mea	n equation of LS	EDR (6)	w9,4	0.10208***	0.00000
w2,9	-0.00191	0.97820		Coefficient	P-values	w9,5	-0.04659***	0.00000
w2,10	0.08293**	0.01659	w6,1	-1.79148***	0.00000	w9,6	0.00520	0.38885
w2,11	-0.44538***	0.00300	w6,2	-0.00266	0.96742	w9,7	0.00580	0.73935
C	1.97134***	0.00314	w6,3	0.29638*	0.06388	w9,8	0.00259	0.75125
Mean eq	uation of DAXN	R (3)	w6,4	0.12474	0.12375	w9,9	0.02092	0.43059
	Coefficient	P-Values	w6,5	-0.14443**	0.02640	w9,10	-0.14959***	0.00000
w3,1	-0.12949*	0.06898	w6,6	0.04398	0.15727	w9,11	-0.12310**	0.02055
w3,2	0.25525***	0.00000	w6,7	0.03243	0.71819	C	0.53745**	0.01967
w3,3	-0.04983**	0.03486	w6,8	0.03200	0.44759	Mear	n equation of NK	DR(10)
w3,4	-0.16898***	0.00000	w6,9	0.08254	0.54615		Coefficient	P-Values
w3,5	0.00670	0.48544	w6,10	0.03611	0.59334	w10,1	0.47758**	0.02172
w3,6	-0.00063	0.89107	w6,11	-0.78042***	0.00590	w10,2	0.10940***	0.00000
w3,7	-0.01018	0.44294	Ċ	3.26882***	0.00430	w10,3	0.04984	0.47018
w3,8	0.00154	0.80418	Mea	n equation of SS	ENR (7)	w10,4	0.10053***	0.00000
w3,9	0.00309	0.87850		Coefficient	P-values	w10,5	-0.01038	0.71154
w3,10	-0.06087***	0.00000	w7,1	0.70796***	0.00000	w10,6	0.01009	0.45204
w3,11	-0.03689	0.31271	w7,2	0.28294***	0.00000	w10,7	-0.00094	0.98057
C	0.17700	0.36164	w7,3	0.05464	0.17716	w10,8	-0.03692**	0.04227
Mean eq	uation of DAXD	R (4)	w7,4	0.04158**	0.04268	w10,9	0.06272	0.28780
	Coefficient	P-Values	w,7,5	0.02754*	0.09448	w10,10	-0.15462***	0.00000
w4,1	-0.48411**	0.04815	w7,6	-0.00516	0.51224	w10,11	0.32685***	0.00365
w4,2	-0.00008	0.99807	w7,7	-0.00440	0.84660	Ċ	-1.48924***	0.00568
w4,3	-0.04709	0.56227	w7,8	0.08253***	0.00000			
w4,4	-0.01928	0.63957	w7,9	0.01963	0.57077			

\*, \*\*, \*\*\* denotes 10%, 5%, and 1% level of significance.

Here, number 11 denotes the exogenous variable of the global OIL prices series

Source: Author's calculation.

Nevertheless, SPDR (w3, 2) indicated a positive impact on DAXNR. The inspection demonstrated that an upsurge in DAXDR (w5, 4) and SSEDR (w5, 8) brings a decline in LSENR. Furthermore, an increase in SPNR (w7, 1) and SPDR (w7, 2) has an encouraging mark on SSENR. Besides, SPNR (w9, 1), SPDR (w9, 2), DAXDR (w9, 4), and LSEDR (w9, 6) contained a direct impact on NKNR, but DAXNR publicized an indirect correlation with NKNR. The research reconnoitered that one period lagged values of SPNR and LSEDR have a positive influence, but lagged

values of DAXNR and NKDR have a bad impression on their own current returns. The deviations in global oil prices bring diminution in SPNR and LSENR but intensify the SPDR, LSEDR, and SSEDR. (Peng & Ng, 2012) testified that stock returns of FTSE-100, Nikkei 225, DAX 30, and S&P 500 are intersected. (Natarajan et al., 2014) also noted that returns of US equity markets substantially impact German markets.

The fallouts of returns transmission during the GFC period are unveiled in Table 3 The values showed that SPNR possessed biventral ties with DAXDR, SPDR, and LSEDR. Moreover, SPNR and LSENR significantly quiver to DAXNR and SSENR, and vice versa. Further, NKDR has bivalence and positive liaison with SPDR but a negative connection with SSEDR. The examination revealed that variations in DAXDR (w3, 4) and NKDR (w3, 10) have a negative and significant impact on DAXNR, and LSEDR (w4, 6) has a positive impact on DAXDR. Besides, spiraling in returns of SPNR (w5, 1), DAXNR (w5, 3), DAXDR (w5, 4), and NKDR (w5, 10) carries a decline in LSENR.

However, SPDR (w5, 2) positively links LSENR. Also, SPNR (w7, 1), SPDR (w7, 2), DAXDR (w7, 4), and SSEDR (w7, 8) confirmed sanguine affiliation with SSENR and DAXNR (w8, 3); while NKNR (w8, 9) showed crucial attachment with SSEDR. The mean equation of NKNR delineated that SPDR and DAXNR positively sway NKNR, but LSENR and NKDR negatively control the NKNR. However, SPNR (w10, 1) and DAXDR (10, 4) retain a positive mark on NKDR. The assessment stripped that returns of SPNR, SPDR, DAXNR, SSEDR, and NKDR at time t-1, obsessed negative effect on personal returns at time t. What is more, the discrepancy in oil prices exposed a negative impact on SPDR, NKDR, SSEDR, SSENR, LSEDR, and NKNR but a positive impact on NKDR. Qarni and Gulzar (2018) uncovered extensive transmission of financial returns from Chinese markets to US markets. Ying Qiana and Francis Diazb (2017) employed BEKK-GARCH, CCC-GARCH, and DCC-GARCH models and established that the US and Europe stock markets were highly integrated.

Table 4 defines the outcomes of Eq. 5. The study found that intercept ( $\mu$ ) values of all stock returns are significant except DAXNR, DAXDR, and LSEDR, which reveals that mean values are different from zero. The domino effect displayed that the volatility of SPNR has a bidirectional and negative impression on the variance of DAXDR and NKNR; also, the volatility of NKDR has a negative and bidirectional risk spillover relationship with LSENR's impulsiveness. Besides, risk spillover from DAXNR (n1, 3) and NKDR (n1, 10) significantly sways the volatility of SPNR. While the volatility of SPNR (n2, 1) and NKDR (n2, 10) showed negative, the volatility of SSEDR exerts a positive influence on the fluctuations of SPDR. The upshots quantified that risk spillover of DAXNR (n4, 3), LSENR (n4, 5), and NKNR (n4, 9) negatively deviates the variability of DAXDR. Additionally, the shocks figured through the standardized residuals of DAXDR (n2, 4), LSENR (n2, 5), and LSEDR (n2, 6) significantly spillover the instability of SPDR. The GARCH ( $\delta 1$ -  $\delta 10$ ) elements of all the stock returns are significantly positive and near to unity, which indicates that the shock effect persists for long-term periods in these markets, except LSEDR, which confirms fair value, i.e., 0.762. These results are in line with the study of (Natarajan et al., 2014) and (Dedi & Yavas, 2016). Further, the positive and significant gamma coefficient for all markets signifies the symmetric impact for these markets during a stable period. Moon and Yu

Table 4.	Results of DCC-N	MEGARCH mo	odel (panel /	A).							
	Coefficient	P-values		Coefficient	P-values		Coefficient	P-values		Coefficient	P-values
µ1	-0.0219**	0.02	u10	1.317***	0.00	n3,6	0.02532*	0.09	n7,5	0.042446	0.21
μ2	-0.0228**	0.01	ψ1	5.005***	0.00	n3,7	0.010492	0.75	n7,6	0.009483	0.62
μ3	-0.037238	0.52	ψ2	6.752***	0.00	n3,8	-0.002535	0.88	n7,7	0.038247	0.14
μ4	0.001738	0.85	ψ3	5.197***	0.00	n3,9	-0.071393	0.30	n7,8	-0.018951	0.49
μ5	-0.00563*	0.09	μ4	5.561***	0.00	n3,10	-0.100145	0.20	n7,9	-0.018049	0.60
9n	0.104936	0.29	ψ5	3.220***	0.00	n4,1	-0.1662**	0.02	n7,10	-0.046546	0.16
μ7	-0.0772**	0.02	ф6	5.795***	0.00	n4,2	-0.070976	0.09	n8,1	-0.031287	0.60
н8	0.0098**	0.01	ψ7	2.677***	0.00	n4,3	-0.077422	0.10	n8,2	-0.035338	0.22
6ц	-0.0078**	0.03	ф8	4.701***	0.00	n4,4	0.074737	0.42	n8,3	-0.006885	0.84
μ10	-0.05283*	0.07	6ψ	6.049***	0.00	n4,5	-0.033063	0.26	n8,4	0.006567	0.76
91	0.256***	0.00	ψ10	5.967***	0.00	n4,6	-0.015889	0.32	n8,5	-0.004877	0.78
92	0.192***	0.00	G	0.003***	0.00	n4,7	0.016217	0.48	n8,6	-0.002402	0.80
<b>J</b> 3	0.111791	0.35	0	0.993***	0.00	n4,8	0.014153	0.31	n8,7	-0.0423**	0.06
94	0.121***	0.00	€	6.8533*	0.05	n4,9	-0.008496	0.73	n8,8	0.1230***	00.0
<b>9</b> 5	0.063***	0.00	n1,1	0.033905	0.37	n4,10	-0.018864	0.44	n8,9	0.012594	0.53
96	0.232483	0.10	n1,2	-0.025893	0.13	n5,1	-0.08190	0.13	n8,10	-0.002949	0.89
97	0.255***	0.00	n1,3	-0.0635**	0.01	n5,2	-0.0643**	0.01	n9,1	-0.1459**	0.01
98	0.097***	0.00	n1,4	-0.0450**	0.04	n5,3	-0.01481	0.63	n9,2	-0.001304	0.97
99	0.063***	0.00	n1,5	-0.055782	0.65	n5,4	-0.0325**	0.06	n9,3	-0.0779**	0.01
<b>∂</b> 10	0.120***	0.00	n1,6	-0.0068	0.63	n5,5	0.0383***	0.00	n9,4	-0.0425**	0.03
δ1	0.990***	0.00	n1,7	0.010656	0.20	n5,6	0.006191	0.59	n9,5	-0.014989	0.33
δ2	0.957***	0.00	n1,8	0.018333	0.31	n5,7	0.002142	0.89	n9,6	0.00971	0.34
δ3	0.965***	0.00	n1,9	-0.0289**	0.01	n5,8	0.002713	0.79	n9,7	0.019282	0.18
δ4	0.968***	0.00	n1,10	-0.064***	0.00	n5,9	0.03117**	0.06	n9,8	-0.014206	0.14
δ5	0.987***	0.00	n,2,1	-0.3401**	0.01	n5,10	-0.0486**	0.01	n9,9	0.0227***	0.00
δ6	0.762***	0.00	n2,2	0.168941	0.41	n6,1	-0.229318	0.32	n9,10	-0.032762	0.11
67	0.962***	0.00	n2,3	0.045268	0.43	n6,2	-0.1154**	0.02	n10,1	-0.105217	0.24
68	0.980***	0.00	n2,4	0.019625	0.76	n6,3	-0.057584	0.48	n10,2	-0.018161	0.58
69	0.986***	0.00	n2,5	-0.008667	0.76	n6,4	-0.078141	0.17	n10,3	-0.011405	0.82
δ10	0.932***	0.00	n2,6	0.004664	0.23	n6,5	0.061905	0.40	n10,4	0.003588	0.91
u1	1.135***	0.00	n2,7	-0.028987	0.48	n6,6	0.203416	0.11	n10,5	-0.0418*	0.09
u2	0.936***	0.00	n2,8	0.011**	0.01	n6,7	-0.059213	0.48	n10,6	0.013035	0.33
u3	1.092***	0.00	n2,9	-0.079459	0.11	n6,8	0.02944	0.26	n10,7	-0.054498	0.15
u4	-0.880***	0.00	n2,10	-0.045*	0.05	n6,9	0.082209	0.25	n10,8	-18565	0.21
u5	1.0572***	0.00	n3,1	-0.183427	0.88	n6,10	-0.055963	0.18	n10,9	-0.028043	0.34
n6	0.8435***	0.00	n3,2	-0.005924	0.18	n7,1	-0.041648	0.67	n10,10	0.12840**	0.02
U7	-0.999***	0.00	n3,3	0.0554*	0.07	n7,2	-0.070583	0.11			
u8	1.1464***	0.00	n3,4	-0.067***	0.00	n7,3	-0.079887	0.17			
00	-1.084***	0.00	n3,5	0.021646	0.39	n7,4	0.001808	0.95			
) *** ' ** '	denotes 10%, 5%, ar	the second of the second se	significance.								
Source: AL	uthor's calculations.										

Confinent         Padles         Coefficient	le 5. Results	of DCC-ME	GARCH mod	del (panel B								
-0554**         0.03         1,4/11***         0.00         7,3         -0.034         0.01         7/1         0.0034         0.03           -01054**         0.01         -0         -0.0541**         0.00         -0.54         -0.0547         0.00         0.03           -01065**         0.01         -0         -0.017**         0.000         0.017**         0.000         0.00         0.000         0.	Coef	ficient	P-values		Coefficient	P-value		Coefficient	P-value		Coefficient	P-value
-0.03731         0.13         -0.0341         0.317         7.75         0.0097         0.36           -0.0357***         0.06         0.4         -0.0344         0.317         0.0175         0.0097         0.36           -0.0357***         0.06         0.4         -1.06****         0.00         0.35         0.011324         0.037         0.0075         0.007         0.36           -0.0311         0.03         0.31         -0.013705         0.013         0.313         0.0175         0.0075         0.0175         0.0175         0.0175         0.0175         0.0176         0.0175	-0.0	524**	0.03	υ5	1.4711***	0.00	n3,3b	-0.253059	0.117	n7,4	0.0034	0.95
-0.1630*         0.00         1/2         0.9330*         0.00         1/3         0.017280         0.044         1/3         0.0007         0.031         0.0173         0.0173*         0.0007	0.0(	09751	0.15	u6	-0.823***	0.00	n3,4	-0.05431	0.317	n7,5	0.0099	0.68
0.005***         0.00         0.3         0.01960         0.203         0.773         0.0177*         0.0077*         0.003           0.003111         0.003         0.1         1.4327***         0.00         0.3         0.031329         0.73         0.0373*         0.0373         0.033           0.00311         0.00         0.1         3.14         0.001144         0.05         0.73         0.0033         0.033         0.0133 <td>-0.1</td> <td>4550*</td> <td>0.07</td> <td>U7</td> <td>0.9802***</td> <td>0.00</td> <td>n3,5</td> <td>-0.012789</td> <td>0.644</td> <td>n7,6</td> <td>0.0200</td> <td>0.38</td>	-0.1	4550*	0.07	U7	0.9802***	0.00	n3,5	-0.012789	0.644	n7,6	0.0200	0.38
0.00067         0.05         0.067         0.057 <t< td=""><td>0.0(</td><td><b>065**</b>*</td><td>0.00</td><td>u8</td><td>0.8850***</td><td>0.00</td><td>n3,6</td><td>0.01969</td><td>0.203</td><td>n7,7a</td><td>0.0170*</td><td>0.09</td></t<>	0.0(	<b>065**</b> *	0.00	u8	0.8850***	0.00	n3,6	0.01969	0.203	n7,7a	0.0170*	0.09
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0	10667	0.96	00	-1.040***	0.00	n3,7	0.031329	0.510	n7,7b	0.0637	0.78
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	50.0	940***	0.00	u10	-1.076***	0.00	n3,8	-0.011194	0.573	n7,8	-0.0572	0.19
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0-	221	0.59	ψ1	3.3060***	0.00	n3,9	0.13724*	0.056	n7,9	0.176*	0.08
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.0	737***	0.00	ψ2	14.532***	0.00	n3,10	-0.033055	0.378	n7,10	0.0059	0.88
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.0	34131	0.29	ψ3	4.3824***	0.00	n4,1	-0.780***	0.000	n8,1	0.1674	0.44
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0(	34944 24	0.66	ψ4	16.022058	0.1519	n4,2	-0.052535	0.155	n8,2	0.0673	0.11
$\begin{array}{lcccccccccccccccccccccccccccccccccccc$	-0.1	20004	0.64	ψ5	3.13297**	0.00	n4,3	-0.036077	0.676	n8,3	0.146**	0.04
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.4	1228*	0.05	ψ6	5.80486**	0.0121	n4,4a	0.0791***	0.000	n8,4	0.077**	0.02
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.35	34***	0.00	ψ7	2.7695***	0.00	n4,4b	0.048612	0.453	n8,5	-0.0231	0.16
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.5(	00261	06.0	ψ8	7.9874***	0.00	n4,5	0.005737	0.758	n8,6	-0.0074	0.52
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.15	52879	0.27	<u>е</u> ф	9.2599***	0.00	n4,6	0.014957	0.251	n8,7	-0.0381	0.25
$ \begin{array}{lcccccccccccccccccccccccccccccccccccc$	0.00	32726	0.98	ψ10	11.0421**	0.0249	n4,7	-0.014945	0.611	n8,8a	0.0771	0.03
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	-0.30	***0C	0.00	3	0.00354*	0.0956	n4,8	-0.000923	0.947	n8,8b	-0.0666	0.42
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.35	965***	0.00	ዮ	0.9549***	0.00	n4,9	0.05571	0.352	n8,9	-0.0755	0.22
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	-0.0-	5464*	0.08	÷	6.8730***	0.00	n4,10	-0.017463	0.530	n8,10	-0.0016	0.97
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.27	21076	0.17	n1,1a	0.04736*	0.0701	n5,1	0.693092*	0.082	n9,1	-0.2352	0.19
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.2(	5281*	0.01	n1,1b	0.082361	0.3994	n5,2	-0.028809	0.754	n9,2	0.0103	0.80
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	-0.0-	74326	0.49	n1,2	0.040052	0.3999	n5,3	-0.009925	0.929	n9,3	-0.0418	0.50
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.1	32755	0.28	n1,3	-0.114249	0.29816	n5,4	-0.039289	0.761	n9,4	-0.0038	0.92
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.0(	04655	0.97	n1,4	-0.0973**	0.03898	n5,5a	0.18212	0.345	n9,5	-0.0105	0.57
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0-	1321	0.91	n1,5	0.038987	0.11271	n5,5b	-0.43044	0.544	n9,6	-0.0157	0.21
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.0	71942	0.56	n1,6	0.03205**	0.03786	n5,6	0.042815	0.102	n9,7	0.02642	0.46
$\begin{array}{llllllllllllllllllllllllllllllllllll$	0.2	4792**	0.01	n1,7	0.07888**	0.03261	n5,7	-0.033431	0.658	n9,8	-0.026**	0.03
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	-0.0	93306	0.39	n1,8	0.001351	0.93432	n5,8	0.08178**	0.014	n9,9a	0.0144*	0.08
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.0	80667	0.36	n1,9	0.055028	0.35750	n5,9	0.190688	0.422	n9,9b	-0.0589	09.0
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.1	4363	0.15	n1,10	-0.03615	0.29658	n5,10	0.025058	0.842	n9,10	0.0144	0.65
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	36.0	885***	0.00	n,2,1	0.019727	0.92423	n6,1	-0.348718	0.770	n10,1	0.0427	0.85
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	0.96	969***	0.00	n2,2a	0.075156	0.51698	n6,2	-0.060713	0.494	n10,2	0.0213	0.63
0.9398***         0.00         n2,3         -0.07413         0.28816         n6,4         -0.00781         0.864         n10,4         -0.0384         0.43           0.5869***         0.00         n2,4         0.077044*         0.09192         n6,5         0.027957         0.611         n10,5         -0.007         0.81           0.5869***         0.00         n2,5         0.01744**         0.09192         n6,5         0.012655         n6,6         0.1156172         0.455         n10,6         0.0116         0.38           0.9401***         0.00         n2,7         0.027655         n6,6         0.102018         0.515         n10,7         0.019         0.65           0.9453***         0.00         n2,7         0.02765         n6,6         0.102018         0.515         0.0116         0.27           0.9453***         0.00         n2,8         -0.07752         0.29668*         0.6671         n10,7         0.019         0.26           0.9556***         0.00         n2,8         -0.07782         0.11410         n6,9         -0.037694         0.556         n10,9         -0.038         0.16           0.9556***         0.00         n2,9         -0.01789         0.610         0.007	.0.9	239***	0.00	n2,2b	-0.058013	0.52568	n6,3	0.044684	0.492	n10,3	-0.141	0.10
0.5869***         0.00         n2,4         0.077044*         0.09192         n6,5         0.027957         0.611         n10,5         -0.007         0.81           0.9401***         0.00         n2,5         0.01744**         0.02556         n6,6a         -0.156172         0.455         n10,6         0.0116         0.38           0.9401***         0.00         n2,7         0.0270**         0.02656         n6,6b         0.102018         0.515         n10,7         0.019         0.65           0.9433***         0.00         n2,7         -0.02752         0.29468         n6,7         -0.037669         0.671         n10,7         0.0176         0.27           0.9555***         0.00         n2,8         -0.0751         0.17310         n6,8         0.0566**         0.048         0.16         0.27         0.28         0.16         0.27         0.28         0.16         0.27         0.28         0.16         0.27         0.28         0.16         0.28         0.27         0.21         0.10,7         0.21         0.21         0.27         0.27         0.28         0.21         0.27         0.28         0.16         0.28         0.28         0.25         0.10,0         0.28         0.16	0.9	398***	0.00	n2,3	-0.07413	0.28816	n6,4	-0.00781	0.864	n10,4	-0.0384	0.43
0.9401***         0.00         n2,5         0.0174**         0.02656         n6,6a         -0.156172         0.455         n10,6         0.0116         0.38           0.9453***         0.00         n2,6         0.0270*         0.0565         n6,6b         0.102018         0.515         n10,7         0.019         0.65           0.9433***         0.00         n2,7         -0.02752         0.29868         n6,7         -0.037669         0.671         n10,8         -0.0176         0.27           0.9453***         0.00         n2,8         -0.01711         0.17310         n6,8         0.0566**         0.048         0.016         0.28           0.9556***         0.00         n2,9         -0.017892         0.11410         n6,9         -0.07284         0.556         n10,10a         0.0469         0.466           0.956***         0.00         n2,1         -0.037872         0.11410         n6,9         -0.07248         0.955         n10,10b         -0.0469         0.466           1.027***         0.00         n3,1         -0.31684         0.18763         n7,1         -0.377907         0.173         0.0469         0.456           0.127***         0.00         n3,1         -0.31763	0.58	869***	0.00	n2,4	0.077044*	0.09192	n6,5	0.027957	0.611	n10,5	-0.007	0.81
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.92	401***	0.00	n2,5	0.01744**	0.02656	n6,6a	-0.156172	0.455	n10,6	0.0116	0.38
0.9439***         0.00         n2,7         -0.02752         0.29668         n6,7         -0.037669         0.671         n10,8         -0.0176         0.27           0.9755***         0.00         n2,8         -0.0151         0.17310         n6,8         0.05066**         0.048         n10,9         -0.088         0.16           0.9556***         0.00         n2,9         -0.0151         0.17310         n6,8         0.0566**         0.048         n10,103         -0.088         0.16           0.9556***         0.00         n2,10         -0.0178872         0.11410         n6,9         -0.070594         0.556         n10,103         0.0469         0.46           1.027***         0.00         n2,1         -0.017899         0.61189         n6,10         0.007248         0.955         n10,10b         -0.046         0.43           -0.900***         0.00         n3,1         -0.31684         0.18763         n7,1         -0.377907         0.173         -0.046         0.43           -1.127***         0.00         n3,2         -0.331684         0.18763         n7,1         -0.377907         0.173         -0.046         0.43           0.874**         0.00         n3,3a         0.061168	<i>•</i> 0.0	453***	0.00	n2,6	0.0270*	0.06765	n6,6b	0.102018	0.515	n10,7	0.019	0.65
0.9755***         0.00         n2,8         -0.0151         0.17310         n6,8         0.0566**         0.048         n10,9         -0.088         0.16           0.9556***         0.00         n2,9         -0.078872         0.11410         n6,9         -0.070594         0.556         n10,10a         0.0469         0.46           1.027***         0.00         n2,10         -0.017089         0.61189         n6,10         0.007248         0.955         n10,10a         0.0469         0.46           -0.900***         0.00         n3,1         -0.017089         0.61189         n6,10         0.007248         0.955         n10,10b         -0.046         0.43           -0.900***         0.00         n3,1         -0.31684         0.18763         n7,1         -0.377907         0.173         0.0469         0.43           -1.127***         0.00         n3,2         0.0337922         0.48973         n7,2         0.015402         0.773           0.874**         0.00         n3,3a         0.50474         n7,3         -0.081761         0.453	0.9	439***	0.00	n2,7	-0.02752	0.29868	n6,7	-0.037669	0.671	n10,8	-0.0176	0.27
0.9596***         0.00         n2,9         -0.078872         0.11410         n6,9         -0.070594         0.556         n10,10a         0.0469         0.46           1.027***         0.00         n2,10         -0.017089         0.61189         n6,10         0.007248         0.955         n10,10b         -0.046         0.43           -0.900***         0.00         n3,1         -0.31684         0.18763         n7,1         -0.377907         0.173         -0.046         0.43           -1.127***         0.00         n3,2         0.0337922         0.48973         n7,2         0.015402         0.773           0.874**         0.00         n3,3a         0.061168         0.50474         n7,3         -0.081761         0.453	0.97	755***	0.00	n2,8	-0.0151	0.17310	n6,8	0.05066**	0.048	n10,9	-0.088	0.16
1.027***         0.00         n2,10         -0.017089         0.61189         n6,10         0.007248         0.955         n10,10b         -0.046         0.43           -0.900***         0.00         n3,1         -0.331684         0.18763         n7,1         -0.377907         0.173         -0.046         0.43           -1.127***         0.00         n3,2         0.037922         0.48973         n7,2         0.015402         0.773           0.874**         0.00         n3,3a         0.061168         0.50474         n7,3         -0.081761         0.453	-0.9	596***	0.00	n2,9	-0.078872	0.11410	n6,9	-0.070594	0.556	n10,10a	0.0469	0.46
-0.900*** 0.00 n3,1 -0.331684 0.18763 n7,1 -0.377907 0.173 -1.127*** 0.00 n3,2 0.037922 0.48973 n7,2 0.015402 0.773 0.874*** 0.00 n3,3a 0.061168 0.50474 n7,3 -0.081761 0.453	1.02	27***	0.00	n2,10	-0.017089	0.61189	n6,10	0.007248	0.955	n10,10b	-0.046	0.43
-1.127*** 0.00 n3,2 0.037922 0.48973 n7,2 0.015402 0.773 0.874*** 0.00 n3,3a 0.061168 0.50474 n7,3 –0.081761 0.453	-0.9(	***0C	0.00	n3,1	-0.331684	0.18763	n7,1	-0.377907	0.173			
0.874*** 0.00 n3,3a 0.061168 0.50474 n7,3 –0.081761 0.453	-1.1	27***	0.00	n3,2	0.037922	0.48973	n7,2	0.015402	0.773			
	0.87	74***	0.00	n3,3a	0.061168	0.50474	n7,3	-0.081761	0.453			

<sup>\*, \*\*, \*\*\*</sup> denotes 10%, 5%, and 1% level of significance. Source: Author's calculations.

(2010) discovered the symmetric spillover effect from Chinese markets to the US. Further, (P. Wang & Wang, 2010) reported the symmetric effect for Japan and the US.

As well, the statistically significant and positive ARCH coefficient of DAXNR (n3, 3), LSENR (n5, 5), SSEDR (n8, 8), NKNR (n9, 9), and NKDR (n10, 10) stipulates that shocks determined through standardized residuals increased the conditional volatility of their own returns in the following day. Besides, the sum of assessed DCC coefficients  $\omega$  and  $\vartheta$  is significantly positive and less than unity, which verifies that our model is mean-reverting. This study seized the negative skewness of DAXDR, SSENR, and NKNR. Moreover, the degree of freedom parameter is moderate and significant, which means this assignment has successfully apprehended the actual fat-tailed returns distribution of these stock markets. (Li, 2007) and (Moon & Yu, 2010) captured the positive skewness values for the US and Chinese stock markets.

Table 5 pageants the fallouts of the variance equation for the period of GFC. The study used the MEGARCH (2, 1) model based on the Akaike information criterion for the period of GFC.<sup>2</sup> The findings stated that shocks befallen in DAXDR have negative and bidirectional spillover liaison with the variance of SPNR. Likewise, the volatility of LSEDR (n1, 6) and SSENR (n1, 7) significantly amplifies the instability of SPNR. Also, the risk ascended due to DAXDR (n2, 4), LSENR (n2, 5), and LSEDR (n2, 6), significantly moving the volatility of SPDR in an upward direction. Also, the shocks that occurred in SSEDR showed significant bonding with the conditional variance of LSENR (n5, 8) and LSEDR (n6, 8). However, the volatility of DAXNR (n8, 3) and DAXDR (n8, 4) have positive and significant impacts on the variance uncertainty of SSEDR. The investigation explored that the volatility of NKNR significantly spillovers the volatility of DAXNR (n3, 9) and SSENR (n7, 9). At the same time, the variance changes of SPNR have a positive liaison with the variance change of LSENR (n5, 1). Further, the volatility of SSEDR showed a negative connection with the volatility of NKNR (n9, 8). The coefficients ( $\delta 1$  to  $\delta 10$ ) indicated that these markets have a significant GARCH effect, meaning that previous volatility has a striking impact on the present-day volatility of personal returns. The significant ARCH elements of SPNR (n1, 1), DAXDR (n4, 4), SSENR (n7, 7), SSEDR (n8, 8), and NKNR (n9, 9) enunciate that the shocks figured by standardized residual significantly upset the volatility of their own returns in the subsequent period ((Mohammadi & Tan, 2015)). Furthermore, significant and negative first-moment gamma parameters of SPDR ( $\partial 2a$ ), DAXDR ( $\partial 4a$ ), and LSENR ( $\partial 5a$ ) implied that adverse shocks have more influence

Table 6. Time-varying correlation (panel A).

		, , , .	· · · · · · · · · · · · · · · · · · ·	- /						
	SPNR	SPDR	DAXNR	DAXDR	LSENR	LSEDR	SSENR	SSEDR	NKNR	NKDR
SPNR	1									
SPDR	0.22623	1								
DAXNR	0.50656	0.15080	1							
DAXDR	0.38135	0.43214	-0.0083	1						
LSENR	0.19744	0.05779	0.25982	0.03623	1					
LSEDR	0.16183	0.22443	0.0245	0.30060	0.0050	1				
SSENR	0.17566	-0.0102	0.2228	-0.0219	0.0954	-0.0303	1			
SSEDR	0.22308	0.02545	0.3035	-0.0231	0.0656	0.05164	0.06962	1		
NKNR	0.14286	0.02506	0.2708	-0.0102	0.0383	-0.0219	0.25534	0.0486	1	
NKDR	0.31870	0.14489	0.4505	0.0025	0.14540	0.00979	0.13808	0.2203	0.0747	1

Source: Author's Calculation.

<sup>2</sup>We used the Akaike information criterion to choose the best lag model and found that MEGARCH (2, 1) model has a minimum value for the period of Global Financial Crises. More information can be provided on demand.

	SPNR	SPDR	DAXNR	DAXDR	LSENR	LSEDR	SSENR	SSEDR	NKNR	NKDR
SPNR	1									
SPDR	0.2973	1								
DAXNR	0.3917	0.1788	1							
DAXDR	0.4146	0.6352	0.178	1						
LSENR	0.1422	-0.0174	0.2730	0.0455	1					
LSEDR	0.1631	0.3608	0.1154	0.4111	-0.0782	1				
SSENR	0.0703	-0.0063	0.0815	-0.0240	-0.0136	-0.0318	1			
SSEDR	0.1286	0.0548	0.2588	0.0355	0.0629	0.0346	-0.002	1		
NKNR	0.1592	0.0460	0.3343	0.0197	0.0538	0.0360	0.1411	0.0469	1	
NKDR	0.28054	0.1252	0.5054	0.1114	0.1596	0.0505	0.0612	0.1815	0.1575	1

Table 7. Time-varying correlation (panel B).

Source: Author's calculation.

on the volatility of these stock returns as compared to positive shocks of the same magnitude, concluding that the influence is asymmetric and leverage impact exists for these stock returns (R. F. Engle & Patton, 2001). Hence, these results indicated that lousy news affects more during financial crises than good news.



Figure 3a. Time-varying correlation.



Figure 3b. Continued.

The returns distribution of SPDR (v2), DAXNR (v3), LSEDR (v6), NKNR (v9), and NKDR (v10) possessed negative and significant skewness, and others showed positive skewness. Bekiros (2014) mentioned both positive and negative skewness of DAX 30 during different periods. The degree of freedom parameters ( $\psi$ 1 to  $\psi$ 10) are significant and earned an adequate value range from 2.76 to 16.02. Significant DCC parameter  $\omega$  definite that the current volatility of returns has an essential influence on the dynamic



Figure 3c. Continued.

association amongst these markets. The crucial value of parameter  $\vartheta$  is also adjacent to unity, signifying that the dynamic tie concerning these markets would lengthen for an elongated term period (Jiang et al., 2019).

#### 5.2. Time-varying correlation elucidation

Tables 6 and 7 demonstrate the correlation results for the standard and GFC periods, respectively. The end of the standard period stated that SPNR has a positive correlation with all stock returns, whereas SPDR showed a negative affiliation with SSENR. Also, the correlation of DAXDR with DAXNR, SSENR, SSEDR, and NKNR was noted as unfavorable. Although LSENR had a positive correlation with all stock returns, and LSEDR revealed a negative association with SSENR and NKNR. The correlation results during the GFC period specified that SPNR maintained a positive correlation with all stock returns. Moreover, DAXDR has a positive association with DAXNR, SSEDR, and NKNR, but during the standard period, it exposed a negative relationship with these stock returns. Also, the correlation between LSEDR and NKNR turns out to be positive, whereas, in the course of a stabled era, it displayed negative affiliation with each other. Besides, NKDR possessed a positive linkage with all stock returns.

Figure 3a, 3b, 3c exhibited the time-varying correlation among these stock reruns for panel A. The upshots highlighted that the correlation of SPNR with DAXNR, DAXDR, SSENR, SSEDR, and NKDR is positive over the period. Nonetheless, the correlation between SPNR and NKNR goes negative at the beginning of 2014. Moreover, the correlation pattern between LSENR and SPNR is expressively different from the correlation pattern between LSEDR and SPNR. Furthermore, the correlation between SPDR and DAXNR reached a maximum value of 0.30, and

Panel A					Panel B				
Variable	Q (20)	P-values	Q2 (20)	P-values	Variable	Q (20)	P-values	Q2 (20)	P-value
SPNR	25.984	0.20	16.585	0.6797	SPNR	16.439	0.689	18.636	0.5456
SPDR	27.556	0.12	8.2081	0.9904	SPDR	8.3762	0.9891	15.426	0.7515
DAXNR	60.65	0.1438	13.412	0.859	DAXNR	17.347	0.6304	5.3129	0.9996
DAXDR	19.873	0.4659	21.087	0.392	DAXDR	24.431	0.2241	23.848	0.2491
LSENR	10.931	0.948	0.37277	1.000	LSENR	25.015	0.2009	0.98293	1.0000
LSEDR	13.593	0.8505	15.282	0.7601	LSEDR	17.075	0.6481	13.505	0.8547
SSENR	0.57475	0.9022	9.1675	0.9809	SSENR	36.88**	0.01207	50.22***	00000
SSEDR	59.694	0.1639	138.3***	00000	SSEDR	27.769	0.115	9.121	0.9815
NKNR	27.108	0.1323	17.716	0.6061	NKNR	15.594	0.7415	23.634	0.2587
NKDR	22.271	0.326	6.2211	0.9986	NKDR	20.617	0.42	13.759	0.8425

Table 8. Back-testing of the VARX-DCC-MEGARCH model.

\*, \*\*, \*\*\* denotes 10%, 5%, and 1% level of significance.

Source: Author's calculations.

Source: Author's Calculation.

the correlation between SPDR and DAXDR attained a maximum value of 0.60. Further, the correlation between SPDR and LSENR is less strong than the correlation between SPDR and LSEDR. The correlation of SPDR has gone negative with SSENR, SSEDR, and NKNR but remains positive with NKDR. The outcomes about the correlation history of DAXNR discovered that it has a positive liaison with LSENR, SSENR, SSEDR, NKNR, and NKDR, but it went negative with LSEDR during the year 2012. Additionally, the correlation of DAXDR with SSENR, SSEDR, and NKNR persisted negative for most of the periods. In contrast, the correlation of LSENR with SSENR, SSEDR, NKNR, and NKDR sustained positive. However, the correlation between LSEDR and SSENR becomes negative in the end. Nonetheless, the correlation between LSEDR and NKDR remained positive during the whole time. Also, the correlation of SSENR with NKNR and NKDR and SSEDR with NKDR was positive. However, the correlation between SSEDR and NKNR was reported as unfavorable at the beginning of 2019. Consequently, these upshots verified the time-varying correlation among financial markets

#### 5.3. Performance assessment of the VARX-DCC-MEGARCH model

In order to ascertain the serial correlation in standardized residuals and the square of standardized residuals, this investigation applied the Ljung-Box test at lag 20. The consequences in Table 8 acknowledged that there is no serial correlation between the standardized residuals and the square of standardized residuals for both panels. Accordingly, the statistics produced by the VARX-DCC-MEGARCH models are correct, and the model is correctly fitted.

#### 6. Conclusion, policy insinuations, and future recommendations

The information has a momentous sway on financial markets performance, and stock proceeds devour a substantial impact on a country's economy. It has become essential to have comprehensive information about their actions and magnetic attachments. Therefore, by developing the multivariate econometric model, this study investigated the returns transmission, volatility spillovers, leverage effect, optimal portfolios, portfolio VaR and dynamic correlation among the systemic financial markets of the US, London, Japan, Germany, and China. This research applied the VARX-DCC-MEGARCH model assimilated with a skewed-t density and discovered that current day-wise returns of SSEC (SSEDR) negatively influence the subsequent overnight returns of the S&P 500 index (SPNR) and vice versa. The trade war between China and the US can be a significant reason for this negative association. This relationship can also be due to contrary sensitivities to variation in the interest rate, or these markets respond differently to external stimuli. While during crises, this liaison was found to be insignificant. It postulates that the stock markets of China and the US have profitable options for the US and Chinese investors to maximize their returns. The novel daytime returns transmission from DAX 30, FTSE 100, and Nikkei 225 index to succeeding overnight returns of the S&P 500 index was insignificant during the stable period, but during GFC, they were found to be significant. Hence, it acquaints that overnight returns of the S&P index provide profitable trading opportunities to Germany, London, Japanese, and China investors. Furthermore, during the GFC period, present daytime returns of the FTSE 100 index showed a bivariate relationship with resulting overnight returns of the S&P 500 index. However, during the standard period, these relationships do not exist. Consequently, this study argued that during regular periods, S&P 500, DAX 30, Nikkei 225, SSEC, and FTSE 100 provide profitable trading opportunities, but these stock markets become more complex during financial crises. The study stated that returns affiliation of LSENR with SPDR, DAXDR, DAXNR, SSEDR, and NKDR remains significant and negative. Hence, these outcomes revealed that the time difference between London, Germany, China, and Japan imperatively benefits, generating more returns. The reason behind this relationship can be the ratio of the stock market capitalization of the London stock exchange globally. Moreover, close competition of London stocks with these markets can also be a reason for adverse impact. The study indicated that oil prices typically bore adverse effects on both panels' stock returns.

The study also quantified that shocks befallen in the current overnight returns of the S&P 500 partake bidirectional and negative ties with shocks that occurred in subsequent day-wise returns of the DAX 30 index. Likewise, the daytime volatility of FTSE 100 positively moves the overnight instability of DAX 30, while other markets do not spillover the volatility of DAX 30. Hence, it allows US and German investors to expand their risk in these markets. However, the FTSE 100 index is a recipient of volatility from the S&P 500, DAX 30, and Nikkei 225. The examination also dogged that no stock market significantly distressed the overnight variance of the SSEC. Hence, during the standard time, investment in DAX 30, with the concoction of overnight returns of the SSEC, daytime returns of S&P 500, FTSE 100, and Nikkei 225 index, is the best option to diversify risk and gain maximum profit. However, during crises, overnight returns of SSEC with an amalgamation of FTSE 100 and daytime returns of DAX 30 can diversify financial risk.

The study revealed that during the stable period, good news has more impel on these stock returns. However, during the GFC period, the study found a leverage effect for the day-wise returns of the S&P 500, DAX 30, and overnight returns of the FTSE 100 index. Hence, the study clinched that the financial risk in these markets is high as equated to normal circumstances during financial crises. Consequently, these findings provide

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valuable knowledge to prospective US, UK, Japanese, China, and German investors to make a rational decision concerning risk diversification in turbulent and regular periods.

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#### **Notes on contributors**

*Xiaoxing Liu:* Professor Xiaoxing Liu is performing his duties as a leading professor at the School of Economics and Management, Southeast University.

*Khurram Shehzad:* Khurram Shehzad is working as a Ph.D. scholar at the School of Economics and Management, Southeast University.

#### ORCID

Khurram Shehzad (D) http://orcid.org/0000-0001-7835-5264

#### Data availability statement

The data that support the findings of this study are openly available at https://finance.yahoo.com/.

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