Dependence Structure and Volatility Spillover Between Financial Markets of China and Other One Belt One Road Countries

Madiha Niaz[1], Safia Nosheen[2] and Muhammad Ather Ashraf[3]

https://doi.org/10.62345/jads.2024.13.2.28

Abstract

One Belt One Road (OBOR) is an international cooperation program initiated by Xi Jinping (Chinese president) in 2013, aiming to create economic trade, promote regional cooperation, and enhance regional markets' effectiveness. OBOR covers over 70 countries (2/3 of the world's population) and approximately a third of the world's GDP (Du & Zhang, 2018). This study aims to investigate the correlations, volatility spillover, and spillback between China and OBOR initiative countries to measure the time-varying behavior in the financial markets. Two financial markets, i.e., the stock market and the foreign exchange, were selected for the study. 6x countries (each representative of one corridor) having maximum trade based on their balance of trade values were chosen for this study. DCC M GARCH model and copula were applied for this study's analysis. R programming is used for data analysis using R-studio. All sample financial markets showed an asymmetric dependence on China's financial markets, and this dependence increases during financial crises or shock periods compared to good times. All financial markets also indicated two-way time-varying volatility spillover effects in the long run. The financial crises may further intensify these spillover effects.

Keywords: Spillover, Spillback, Dependence, One Belt One Road.

Introduction

One Belt One Road (OBOR) is an international cooperation program initiated by Xi Jinping (Chinese president) in 2013, aiming to create economic trade, promote regional cooperation, and enhance regional markets' effectiveness. This initiative is also known as the Belt Road Initiative (BRI). It is considered one of history's most significant investment and infrastructure projects. OBOR covers over 70 countries (2/3 of the world's population) and approximately a third of the world's GDP (Du & Zhang, 2018). The initiative has recently improved regional ties and enhanced economic growth through regions of Asia, Africa, and Europe (Tsui et al., 2017). The primary aims of this initiative include promoting connectivity between the three continents and their nearby areas, establishing and building strong partnerships, setting up all-dimensional connectivity, and setting up diversified and independent developmental activities in these regions (Sarker et al.,

[1]*PhD Scholar, Hasan Murad School of Management, University of Management and Technology, Lahore. Email: madiha.niaz001@gmail.com*
[2]*Associate Professor, Hasan Murad School of Management, University of Management and Technology, Lahore. Email: safia.nosheen@umt.edu.pk*
[3] *Assistant Professor, Hasan Murad School of Management, University of Management and Technology, Lahore. Email: ather.ashraf@umt.edu.pk*

Compliance with ethical standards: There are no conflicts of interest (financial or non-financial). This study did not receive any funding.

2018). The annual growth of China after BRI has increased to $2.07 trillion (2022) compared to $1.04 at the time of initiation of this agreement. Due to this continuous economic and trade cooperation expansion between China and OBOR economies, there is widespread concern about its environmental impacts.

Financial integration has increased between the international economies in the past 30 years (Billio et al., 2017). In addition, economic and financial interlinkages have also grown substantially between the emerging and developed markets. Panda et al. (2019) explained that rapid globalization in global financial markets is the reason for international financial integration. This openness and integration of the financial markets contribute to economic development (Hung, 2021).

The economic and financial markets also became more interdependent with the acceleration of the development of partnerships and increased trade relationships among the OBOR region. China, the dominant trading partner of the OBOR project, has established corporate relations and maintained resources with financial institutions (like BRICS, NDB, and AIIB) to highlight the importance of financial interactions. OBOR initiative countries can be distributed into six central regions based on their geographic locations, now called the six economic corridors based on locations of South Asia, Southeast Asia, West Asia, Central Asia, East Europe, and Northern Africa. Trade flows to OBOR economies have dramatically increased due to simple trading procedures, reducing trade barriers and trading costs (Ramasamy & Yeung, 2019). Increased financial liberalization and removing constraints from the flow of foreign portfolio investments, foreign direct investments, and exchange rate control have improved economic development (Liu et al., 2017).

With all the benefits of financial integration, it also has some negative impacts, like increased risk levels, which lead to increased correlations, co-movements, and contagion between assets through information spillovers, creating a strong need for diversification (Panda et al., 2019). The theory of portfolio diversification developed by (Markowitz, 1952) suggested that the risk of a portfolio can be minimized by diversified asset allocation. Primarily, diversification strategies were applied within the borders of countries. Still, with increased globalization and advancement in information and communication technologies, the need for global diversification arose, and now global diversification is much preferred than it was 30 years ago (Hanif & Sabah, 2020). Financial integration between markets is generally measured with spillovers. *Cross-border financial spillovers* are situations in which prices of financial assets fluctuate in one economy, causing prices in the same assets or other assets in another economy (Agénor & Pereira da Silva, 2021). Existing literature indicates that these spillovers are time-varying and significant from the US to other world markets (Antonakakis et al., 2018; Ji et al., 2019; Li et al., 2021).

Previous studies have explored financial market interdependence, focused on price, volatility returns, and volume of trading, and considered volatility as a market sentiment/ risk indicator (Fang et al., 2021; Hung, 2019; Jebran & Iqbal, 2016; Mitra, 2017). Studies for co-integration and spillovers initially started in developed economies and found mixed results (Karolyi, 1995; Lin et al., 1994; McMillan, 2020). Some studies concluded that emerging economies allow investors to diversify internationally and minimize risk (Steinberg, 2018; Vo & Tran, 2020). Ng (2000) researched volatility spillovers in Pacific-Basin countries and found that regional factors also cause volatility spillovers apart from world factors. Previous studies have taken into consideration trade associations like the European Union (EU), BRICs, G17, G20, and ASEAN economies to study integration and spillover effects (Kirkulak et al., 2019; Qiu et al., 2017; Vo & Tran, 2020). Many studies have studied China for volatility spillover effects (Chen et al., 2018; Mohammadi & Tan, 2015; Z. Wang et al., 2020; Zhou et al., 2012), but there is scant literature on regional agreement on OBOR, particularly in terms of Volatility spillover of financial markets. The only study conducted by (Lu et al., 2019) researched volatility spillover between China and emerging OBOR countries using the Multiplicative Error Model (MEM) to study the crisis period of 2005-2008.

Although the trade and financial integration between countries was not symmetric, the global financial crises established the concept of a more integrated world with more risk-sharing between regions through better capital allocation, leading to more economic development (Lane & Milesi-Ferretti, 2018). However, as a side effect, they also produced a fragile financial environment and made the long-term growth of economies unstable (Ballester et al., 2019). As OBOR markets develop further, they will exhibit higher co-movements and become more responsive to China's financial markets. During the 1997-98 Asian financial crises, China isolated itself from the Asian markets to avoid its contagious effects. With more interaction between China and other deep regional countries, the risk to financial markets has increased. With complicated financial systems, less mature markets, and more interdependence, the probability of financial spillovers has increased, which may lead to economic turmoil (Patra & Panda, 2021). Also, increased correlations between markets have increased uncertainty levels. Therefore, investors and regulatory bodies need to understand which hedging strategies to implement and how to improve decisions regarding asset allocation.

Considering the above research problem, this study will investigate the correlations, volatility spillover, and spillback between China and OBOR initiative countries to measure the time-varying correlations and spillovers. The concept of spillback is also significantly less researched (Agénor & Pereira da Silva, 2021; Wang et al., 2021). However, the two-way interaction between developed and emerging markets needs to be researched as the world is more integrated. So, the following are the objectives set by the study:

1. To investigate the dependency structure between China's financial markets and other OBOR countries.
2. To investigate the financial market's reaction to shock, volatility transmission, and spillover effects between China and other OBOR countries.
3. To investigate if the volatility spillover effects between China's financial markets and other OBOR countries vary with time.

This research will expand the economic integration and volatility spillover literature by providing empirical evidence on financial integration, dependence structure, volatility spillover, and spillbacks between the financial markets of China and OBOR markets using the M-GARCH Dynamic Conditional Correlation (DCC) model.

This research will increase individual and institutional investors' understanding of risk transmission between OBOR countries. It will also deliver additional insights for asset allocation decisions and edging strategies. Since stock and exchange rate volatility directly interacts with capital market prices, it dramatically impacts an economy's trade and foreign investments. This research will guide economic advisors and decision-makers about changes in volatility patterns and will help in investment and financial decisions regarding risk and return.

The remaining study is organized as follows: section 2 reviews past literature. Section 3 provides the conceptual framework. Section 4 includes research methodology, including various contents like research design, theoretical framework, data collection, population, sample, and explanation of the event window. In section 5, the results are explained and discussed. Conclusions and recommendations for the future will be given in section 6.

Table 1: Summary Of Literature

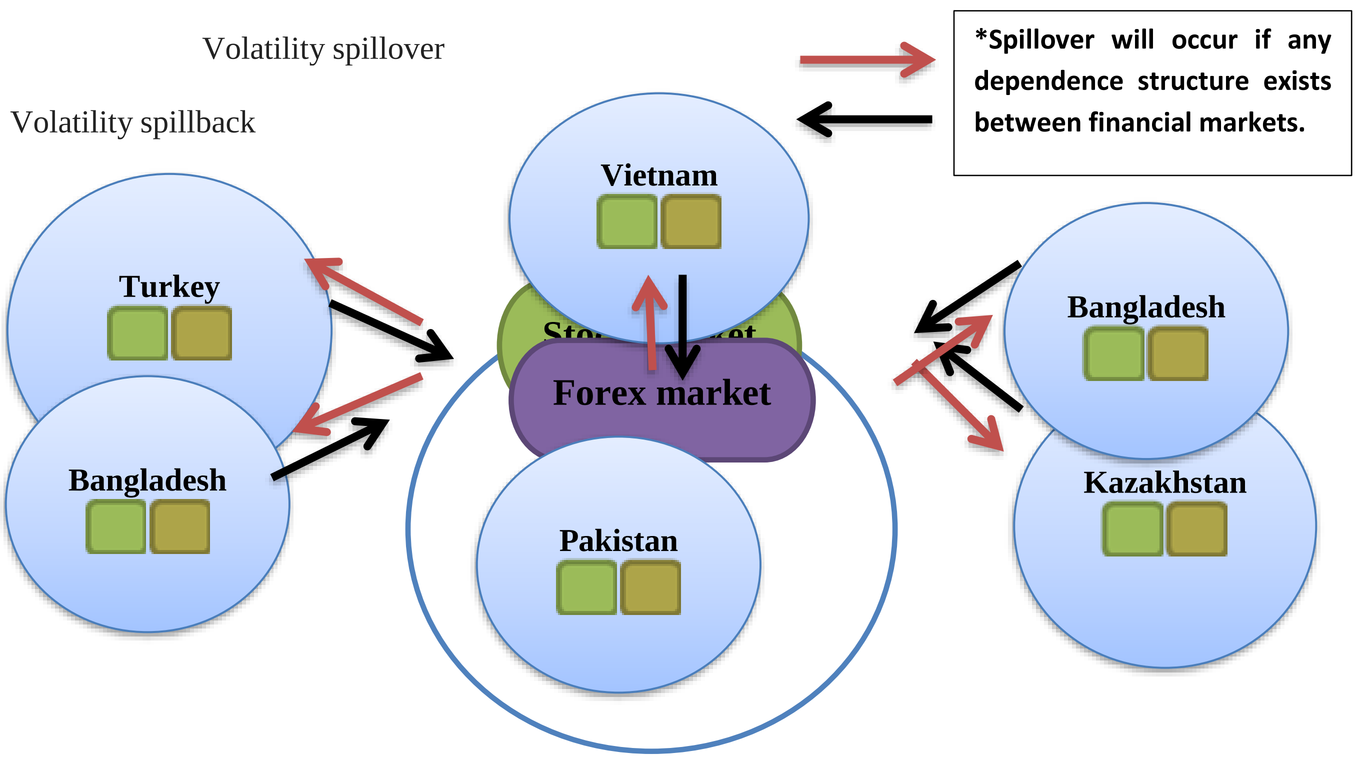
Sr	Concept / Aspect	Studie's Author/ Year	Reseach Question/objective	Research Technique	Outcome
1	Mean and volatility spillover(developed economies)	(Susmel & Engle, 1994)	To analyze timings for mean and volatility spillover effects between London and New York.	ARCH Model	Minimal Volatility spillover between two markets.
2		(Karolyi, 1995)	To study spillover dynamics in New York and Toronto	Multivariate GARCH model	Weak link among the two markets.
3		(Lin et al., 1994)	To study correlation and spillover effects in Tokiyo and New York.	Multivariate GARCH model	Returns of international stock markets were affected by the news released during the trading hours.
4		(McMillan, 2020)	To analyze for causality and spillover between international bond and stock markets of Germany, Japan, US and UK.	VaR models and Granger Causality tests.	Results indicated correlations of same assets across markets rise with time. Whereas correlations across same assets within the country indicated substantial variation.
5		(Li et al., 2021)	To study the volatility spillover effects of interregional Chinese stock markets.	GARCH BEKK model.	Results indicated a significant interregional volatility spillover effect.
6	Return and volatility spillover (Crises Period)	(Yilmaz, 2010)	To analyze East Asian market interdependence and contagion.	rolling window and plotted return and volatility spillover indices.	Returns indicated a major integration between East Asian financial markets whereas volatility index indicated a burst at the time of crises.

7		(Baele, 2005)	To study Western Europe for globalization and integration.	Multivariate GARCH model	Results indicated high shock spillovers between 1980s and 1990s with high spillover intensity to EU shocks.
8		(Syriopoulos et al., 2015)	Analyze financial and industrial sector of BRICS to investigate interrelations and spillover effects.	VAR-GARCH model.	Shock and volatility spillover was found from the US to BRICS with Brazil and Indian economies showing major effects.
9		(Leung et al., 2017)	Analyze exchange rate and equity market during the crisis period to check on the hourly spillover for New York, London, and Tokyo.	Multivariate GARCH model	Positive Volatility spillover effects were found during crises period.
10		(Habiba et al., 2020)	To study the dynamics of Volatility spillover between U.S. and Asian equity markets between the period of financial crises.	EGARCH model.	They found long term integration between the two markets which suggests lower diversification chances for investors during crises period.
11	Mean and volatility spillover(emerging economies)	(Vo & Tran, 2020)	To investigate the ASEAN markets for Volatility spillover effects.	ICSS algorithm model.	Results indicated a strong volatility spread from US to ASEAN economies.
12		(Singh et al., 2010)	To study 15 financial markets to check on the return and VS for the years 2000- 2008.	AR (GARCH) models	Results were consistent for both return and volatility spillover and indicated that US market is affecting most markets.
13		(Roy & Sinha Roy, 2017)	To study the Indian asset market for contagion and VS from commodity market to other asset markets (like bond, gold, forex and equity market).	DCC MGARCH model.	Strong financial contagion was found between commodity and stock market whereas the least contagion was found among gold and commodity market.

14	Volatility Spillback	(Kutlu & Karakaya, 2021)	To study the return and volatility spillover Turkey and Russia.	GARCH and Aggregate Shock model.	Results indicated higher volatility persistence for Russia than Turkey, whereas during the periods volatility persistence is not uniform.
15		(Fang et al., 2021)	To analyze the spillovers/ spillbacks effects from Chinese equity market to G7 countries for bond, stock and forex markets.	VaR frameworks and AR-GARCH model.	Research findings indicated a large variation is created due to spillovers in bond, stock and forex markets which indicated close interconnectedness of financial markets. Chinese markets were also largely affected from the spillbacks of G7 economies. Spillbacks from G7 countries are greater than spillovers by china to G7 economies.
16	Volatility Spillover (pandemic)	(Corbet et al., 2021)	To check the financial market contagion behavior during pandemic using Chinese corona virus/ influenza index.	DCC-GARCH t-Copula	The results indicated an overall effect on the Chinese agricultural, financial energy, Bit coin, gold and oil futures market.

Conceptual Framework

Figure 1: Conceptual diagram

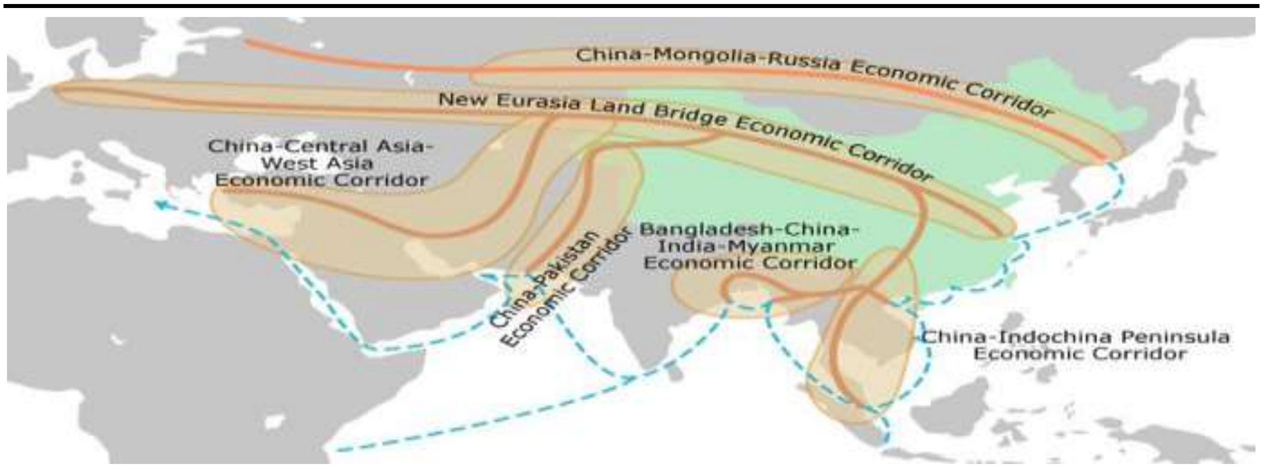


Data and Methodology

Sampling and Data collection

One Belt One Road Initiative comprises six Economic corridors

Figure: 2 World map showing OBOR



Source:https://www.researchgate.net/figure/Six-economic-corridors-of-the-Belt-and-Road-Initiativeurce_fig4_330764703

It is a quantitative study. Moreover, conclusions and results will be derived using statistical procedures (Butt & Yazdani, 2023). All countries included in the six corridors were selected to assess the interdependence and Volatility spillovers. Out of the 19 countries that directly made part of the corridor, 6x countries (each representative of one corridor) having maximum trade based on their balance of trade values were selected for this study. Detail of 6 countries is shown in (Appendix - Table 2). Foreign investments in emerging markets go in different forms, like through stock markets, which aid in equity investments through the purchase of shares, loans through bonds and foreign exchange, etc. Stock prices and exchange rate markets are critical for every economy, contributing to financial development and diversification. Thus, the two financial markets, i.e., the stock market and the foreign exchange market, will be used in this study. The daily closing prices of stocks and exchange rates will be taken, and holidays' values will be removed from the data. The data will be collected from 1st January 2013 to 31st December 2022. R programming will be used for data analysis.

Definition of Variables

Stock Return: Stock returns are defined as the natural log of daily closing prices, i.e., Rt= log pt / pt-1 (El Aal, 2011).

Exchange Rate: The exchange rate is defined as the number of units of domestic currency per unit of foreign currency. An increase in the exchange rate will devalue the domestic currency (Baele, 2005).

Value at Risk: Value at risk is a tool that quantifies a firm's financial risk over a specific period. It is a widely accepted market risk analysis tool that measures stock indices' volatility (Afzal et al., 2021).

Volatility Spillover: Volatility spillover is defined as cross-border circumstances in which variation in prices of financial assets in one economy/ country causes variations in prices of the same financial assets in other economies/ countries(Agénor & Pereira da Silva, 2021).

Volatility Spillback: While observing the spillover effects, some recent studies indicated that emerging economies' financial market shocks (spillovers) have been transmitted back to advanced financial markets (Huang et al., 2018). This condition has been taken as volatility spillback. For this study, spillover from other OBOR countries to China is taken as a Spillback condition.

Methodology

Nanda and Panda (2018) presented the idea that GARCH families have some limitations and are genuinely unable to measure time-varying effects of volatility in dynamic conditions and found asymmetric correlations of stock indices and fatter tail distributions (Ang & Chen, 2002; F. et al., 2000; F. et al., 2001; Tastan, 2006). Using only GARCH models also seems not enough as they also/underestimate forecasting of returns. Afzal et al. (2021) suggested that Dynamic Conditional models can better resolve such issues. Dynamic Conditional Correlation (DCC) captures both volatility clustering and synchronization for financial markets and is a better predictor for capturing market volatility and forecasting VaR. So, the M-GARCH DCC model by Engle (2002) will be used for this study. There are three main benefits of the DCC-GARCH model: a) it accounts for heteroscedasticity by estimating standard coefficients of residual correlation. b) it allows additional explanatory variables to be added to the mean equation to ensure the function is described correctly. c) it can analyze multiple asset returns without incorporating too many variables in the multivariate GARCH method (Cappiello et al., 2006).

Copula models will be applied to overcome the problem of tail dependence. The copula theory was introduced by (Sklar, 1973) and later embraced by (Embrechts et al., 1999; Frey & McNeil, 2003). Embrechts et al. (1999) applied copula theory to returns of financial assets, and later, the model was applied to the time-varying nature of financial dependence (Patton, 2004). The Gaussian and student copulas are used to calculate the time-varying correlation matrix in combination with the DCC model. The copula model enables a flexible multivariate distribution with different margins and dependence structures. By doing this, a joint distribution of portfolios will be created, fulfilling assumptions of normality and correlations. So, in this study, an M-GARCH DCC copula framework model will be applied to measure stock and foreign exchange market volatility spillover indices.

The stock market data for this study has been collected from a) Vietnam stock market (VNINDEX Index), b) BIST stock exchange (XU100 Index), c) the Dhaka stock exchange (DSEX Index), d) the Pakistan stock exchange (KSE100 Index), e) Kazakhstan stock exchange (KASE Index), f) Mongolia stock exchange (MSETOP Index) and g) Shanghai Stock exchange (SSE Index). For foreign exchange historical prices, Central banks relative to the US dollar (to create uniformity in data) along with currency were collected i.e., a) State *Bank of Vietnam* (SBV)/ Dong b) The Central Bank of the Republic of Turkey (CBRT)/ Lira c) Bangladesh Bank/ Taka d) State Bank of Pakistan (SBP)/ Rupee, e) National Bank of the Republic of Kazakhstan (NBK)/ Kazakhstani Tenge f) The Bank of Mongolia/ Mongolian Tugrik and g) Peoples Bank of China (PBOC)/ Chinese Yuan. Total Observations of log returns are 34482 for the period from 2013 to 2020 have been considered. R-studio is used for data testing and analysis. Since emerging economies are highly volatile, volatility clustering will be present in these markets, as shown in Figure 3 a) to n). To determine whether the ARCH effect is present in the data, the Ljung-Box test has been performed, and the results are depicted in table 3. By looking at the test results, it is confirmed that volatility clustering exists in all stock and foreign exchange return data. Similarly, the ARCH test was applied to check on the presence of volatility clustering (ARCH effect), and the results indicated the presence of the ARCH effect in the data.

The stock and forex return have been calculated using the formula:

$$Rt = \left[\log\left(\frac{P1,t+\tau}{P1,t}\right), \dots \dots \dots, \log\left(\frac{Pn,t+\tau}{Pn,t}\right)\right] = R1_t, \dots \dots \dots \dots, RN_t \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(1)$$

The return of stock/ forex 1 is indicated by R1 and RN for Nth Stock/ forex return. The time period is indicated by t. Return after time t is indicated by Rt. To do analysis on financial data it is expected to be independently and equally distributed. Hence, to check the normality of data set Shapiro test was applied. All p-values are less than 0.05 indicating nonnormality in the data as shown in table 3. (T. Aziz et al., 2020)(A. Aziz et al., 2020).

The Q-Q plots were for checking quantiles of normal distribution. On our data set the Q-Q plots (Figure 4) indicated that the goodness of fit is non-linear indicating non normality in the data. Next Jarque- Bera test was applied (Table 3) to the log returns data to confirm the results obtained from Q-Q plots. The null hypothesis of JB test is the data sample data is normally distributed. The results from table 3 indicated rejection of null hypothesis at 5% level of significance. Similarly, Shapiro-Wilk test and kolmogorov-smirnov test also confirmed the rejection of normality and goodness of fit hypothesis for the data set. To make the data set normalized pseudo observations were used for better results (Braarud, 2013). After apply Pobs function in R studio the Q-Q plots are shown as Figure 5.

Last but not the least ADF test was applied to check the presence of stationarity in the data. The null hypothesis of ADF test indicates that unit root is present in the data. The results (table 3) indicated rejection of null hypothesis at 5 % level of signification, that there is no unit i.e. the data is stationary. And the more negative values are indicating a strong rejection of null hypothesis.

To investigate the time-varying correlations DCC-GARCH by (Engle, 2002) is applied. The equation for DCC-GARCH can be represented as:

$H_t = D_t R D_t = \rho_{ij} \sqrt{\ } h_{iit} h_{jjt}$ ……………………………………………………………………... (2)

D_t in equation (1) represents diag($\sqrt{h_{11,t}}$, $\sqrt{h_{22,t}}$,…….$\sqrt{h_{nn,t}}$), which contains time-varying standard deviations from GARCH models.

DCC model has the following structure:

$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2}$ ……………………………………………………………….. (3)

Where

$Q_t = Q + a(z_{t-1} z'_{t-1} - Q) + b(Q_{t-1} - Q)$……………………………………………………..(4)

$= (1 - a - b)Q) + a z_{t-1} z'_{t-1} + bQt\text{-}1$

Table 3: Diagnostic tests

Variable Statistics	**Stock Returns**						
	Shanghai Stock	**VN Index**	**BIST**	**Dhaka Stock**	**KSE**	**KASE**	**MINE**
Jarque - Bera Test	847.87	1385.89	243.85	116.35	1627.11	85.97	7431.24
P – value	0	0	0	0	0	0	0
Shapiro - Wilk Test	0.96	0.95	0.98	0.98	0.96	0.99	0.86
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
kolmogorov-smirnov Test	0.49	0.50	0.49	0.50	0.50	0.50	0.50
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARCH Test	2114.68	2176.83	2164.64	2151.54	2227.38	2143.56	2350.24
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ljung Box Test	2455.71	2460.99	2427.91	2459.43	2454.29	2462.45	2460.16
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ADF Test	-8.48	-9.52	-8.71	-9.60	-9.68	-7.71	-7.79
P – value	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Variable Statistics	**Foreign Exchange Returns**						
	USD_CYN	**USD_VDN**	**USD_TRY**	**USD_BTD**	**USD_PKR**	**USD_KZT**	**USD_MNT**
Jarque - Bera Test	860.64	30055.41	18066.21	59974.93	2058.56	29419.79	3660.42
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shapiro - Wilk Test	0.95	0.72	0.84	0.60	0.87	0.68	0.88
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kolmogorov-smirnov Test	0.50	0.50	0.50	0.50	0.50	0.50	0.50
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ARCH Test	2204.69	2339.64	2028.46	2149.29	2137.55	2121.52	2237.52
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ljung Box Test	2458.54	2458.56	2454.97	2434.12	2457.48	2460.67	2457.83
P – value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ADF Test	-6.88	-9.52	-8.09	-7.86	-9.53	-8.62	-7.35
P – value	0.01	0.01	0.01	0.01	0.01	0.01	0.01

In equation (4) a, b ≥ 0 such that a+b < 1 to indicating stationarity and positive definiteness of Qt. Q denotes unconditional variance-covariance matrix having standardized errors z_t.

Let Xi be any random variable having marginal distribution function fi (i=1,2,3,4………n). According to Sklar (1973) each multivariate distribution function be f (x1, x2,x3…….xn). It can be shown as a marginal distribution function using copula as

$f(x_1, x_2 \ldots, x_n) = C(f_1(x_1), f_2(x_2) \ldots, f_n(x_n))$……………………………………………………..(5)

A copula C having n dimensions having $(0,1)^n$ for distributions f could be defined as:

$C(u_1, u_2, u_3 \ldots\ldots u_n) = f(f_1^{-1}(u_1), f_2^{-1}(u_2), \ldots\ldots f_n^{-1}(u_n))$………………………………………...(6)

for $\forall u_i \in [0, 1]$, i = 1,2,3 . . . , n.

The density functions f and C are shown as:

$f(x_1 x_2, x_3, \ldots, x_n) = C(f_1(x_1), f_2(x_2), f_3(x_3) \ldots, f_n(x_n)) \prod_{i=1}^{n} f_i(x_i)$…………………………………. (7)

$$c(u_1, u_2, u_3 \ldots\ldots u_n) = \frac{f(f_1^{-1}(u_1), f_2^{-1}(u_2), f_3^{-1}(u_3) \ldots, f_n^{-1}(u_n))}{\prod_{i=1}^{n} f_i(f_i^{-1}(u_i))} \qquad (8)$$

f_i in equation (7) and (8) represents marginal densities and f_i^{-1} represents the quantile function of the margins. The study uses two copula families namely the elliptical copula and the Archimedean copula. Elliptical copulas derivate from multivariate elliptical distributions. Gaussian Copula and Student t copula are the most important copulas of Elliptical copula family. The Gaussian Copula C_ρ^{Ev} with a d-dimensional normal distribution and a correlation ρ is a random factor distribution factor ε(x1)…….. ε(xd). ε indicates univariate normal distribution function. So,

$C_\rho^{Ev} = \Psi(\epsilon(x1) \leq u_1, \ldots \ldots \ldots, \in (xd) \leq u_d) = \in_\rho^d (\epsilon^{-1}(u_1), \ldots \ldots \ldots, \epsilon^{-1}(u_d)$……………..…(9)

$\in_\rho^d$ in equation (9) indicates the distribution function of x.

Students t copula $C_{k,\rho}^t$ of a d-dimensional t distribution with k ≥ 0 degree of freedom and ρ correlation matrix indicates the distribution of random vector $t_k(x1) \ldots\ldots t_k(xd)$. Whereas, t_k is a univariate normal distribution and x indicates a $t_d(0, \rho, k)$ distribution.

$C_{k,\rho}^t = \epsilon(t_k(x1) \leq u_1, \ldots\ldots t_k(xd) \leq u_d = t_{k,\rho}^d(t_k^{-1}(u_1), \ldots \ldots, t_k^{-1}(u_d))$………………….(10)

$C_{k,\rho}^t$ in equation (11) indicates the distribution function of x.

Lastly, AIC values are used for the selection of the best fit model (Gabauer, 2020). AIC values can be defined as:

AIC= 2n – 2ln (R) ………………………………………………………………………...(11)

In equation (11) n represents the model parameters and R shows values of the likelihood function. The copula with minimum AIC value will be selected.

Analysis and Results

Descriptive Statistics

Table 5 presents the descriptive statistics of the variables.

Column 1 represents the variable abbreviations for both Stock and foreign exchange markets. Column 2 indicates an equal number of observations for all variable that is 2442. The lower values of standard deviation indicate values are closer to the mean and there is less dispersion. Most of the values of stock exchange prices are negatively skewed except for Bangladesh (DSEX) indicates positively skewed. For forex prices, all values indicates a positive skewness except for Vietnam forex market (USD_VDN) which shows negatively skewed data values. The kurtosis values for stock market are mostly less than 3 indicating a Platykurtic distribution except for Mongolia Stock market (MSETOP) which indicates as Leptokurtic distribution with a value greater than 3. For foreign exchange markets, most of the variable indicate a value greater than 3 that is Leptokurtic distribution except for the China forex market (USD_CYN) which indicates a Platykurtic distribution with a value less than 3.

Tail Dependence using Copulas

Table 6 presents the results of tail dependence using various copulas. According to (Sklar, 1959) copula shows the joint distribution of two variables. The study uses two copula families i.e. a) Elliptical copulas and b) Archimedean copula. Elliptical copulas derivate from multivariate elliptical distributions. Gaussian Copula and Student t-copula are the most important copulas of Elliptical copula family. Whereas Gumbel copula, Clayton copula and Frank copula are used from the Archimedean copula family. The Gaussian copula shows equal degree of positive and negative dependence but lacks in tail dependence therefore modeling with Gaussian copula is similar to estimation of dependence using linear correlation coefficient. Student t-copula indicates non zero symmetric dependence in the tails. It means that dependencies might increase both in bull and bear markets. Student t-copula investigates extreme co-movements between variables and lacks to measure asymmetric dependence. Clayton copula and Gumbel explain asymmetric dependence.
Clayton copula measures the degree of dependence in the lower tail (negative extremes) whereas the Gumbel copula measures the degree of dependence in the upper tail (positive extremes). Frank copula also do not exhibit any tail dependence like Gaussian (normal) copula.
12 combination pairs are used comprising of 6 pairs for stock return indices and 6 pairs for foreign exchange returns. For each pair, the correlation coefficient is indicated by ρ, the degree of freedom (DoF) in t-copula is indicated by μ, the upper tail parameter is indicated by $U\tau$ and lower tail parameter by $L\tau$. Akaike information criteria (AIC), Bayesian information criteria (BIC) and maximum likelihood (LL) are the selection criteria and goodness of fit for copula models. The copula with a maximum value of LL and minimum values of AIC and BIC are the best fitted models.

Table 5: Descriptive Statistics

Stock Returns									
Variable Name	**Number of Observations**	**Mean**	**Median**	**Min**	**Max**	**Range**	**Std. Deviation**	**Skewness**	**Kurtosis**
SSE	2442	0.00017	0.00030	-0.015762988	0.013230981	0.02899397	0.003176566	-0.20306645	2.8531234
VN	2442	0.00034	0.00064	-0.016038472	0.007106721	0.023145193	0.002772597	-1.07903475	2.9880098
BIST	2442	0.00076	0.00075	-0.015869423	0.013247609	0.029117032	0.003556493	-0.01557777	1.5440556
DSEX	2442	0.00018	-0.00002	-0.011732417	0.007396319	0.019128736	0.002327528	0.27963958	0.9080082
KSE	2442	0.00037	0.00051	-0.017764336	0.008892038	0.026656374	0.002708328	-0.80257271	3.6567314
KASE	2442	0.00046	0.00061	-0.009899717	0.00945149	0.019351207	0.002681136	-0.3277817	0.6409621
MSETOP	2442	0.00029	-0.00027	-0.008904681	0.021379126	0.030283806	0.003496414	1.97901282	7.56426
Foreign Exchange Returns									
Variable Name	**Number of Observations**	**Mean**	**Median**	**Min**	**Max**	**Range**	**Std. Deviation**	**Skewness**	**Kurtosis**
USD_CYN	2442	0.00005	-0.00003	-0.002101383	0.002986099	0.005087482	0.000594787	0.81171637	2.4079514
USD_VDN	2442	0.00005	0.00000	-0.002478929	0.002174735	0.004653664	0.000363379	-0.30003202	17.1597511
USD_TRY	2442	0.00096	0.00073	-0.00938014	0.02100603	0.03038617	0.002561381	2.26442613	12.5180128
USD_BTD	2442	0.00011	0.00001	-0.00191236	0.004135497	0.006047857	0.000517799	3.98757969	22.9080698
USD_PKR	2442	0.00034	0.00005	-0.004261225	0.006714133	0.010975358	0.00112842	0.86492429	4.1457137
USD_KZT	2442	0.00046	0.00007	-0.006757612	0.018659684	0.025417295	0.002132264	3.03689686	15.8653965
USD_MNT	2442	0.00037	0.00020	-0.003162155	0.005392466	0.008554621	0.000875648	1.36057726	5.3374076

Table 6: Estimation of Copula parameters and tail dependence

Parameters	Gaussian copula	t-copula	Gumbel copula	Clayton copula	Frank copula	Gaussian copula	t-copula	Gumbel copula	Clayton copula	Frank copula
Stock Return Indices										
	China and Vietnam					**China and Turkey**				
ρ	0.01586	0.5135	1.343	1.042	3.266	0.3503	0.3503	1.196	0.6254	2.249
	0.02	-	0.023	0.037	0.168	0.019	0.019	0.017	0.027	0.135
DoF		4.00					3.31			
Tu		0.41544	0.42267	0			0.36822	0.30442		
Lτ		0.41544	0	0.79623			0.36822	0	0.76796	
AIC	-740.04	-737.96	-376.05	**-857.16**	-652.68	-314.81	-312.59	-135.52	**-372.52**	-321.55
BIC	-734.24	-726.36	-370.25	**-851.36**	-646.88	-309.01	-300.99	-129.72	**-366.72**	-315.75
LL	0.3038	371	189	**429.6**	327.3	158.4	158.3	68.76	**187.3**	161.8
	China and Dhaka					**China and Pakistan**				
ρ	0.2282	0.2276	1.113	0.3458	1.365	0.03582	0.03582	1	0.05461	0.2453
	0.019	0.02	0.015	0.028	0.12	0.021	0.021	0.013	0.025	0.121
DoF		9.19					7.9			
Uτ		0.54146	0.18908	0			0.54808	0.03651	0	
Lτ		0.54146	0	0.74311			0.54808	0	0.71365	
AIC	-127.27	-129.1	-54.311	**-185.76**	-114.9	-1.0998	0.92159	2	**-2.4551**	-2.0554
BIC	-121.47	-117.5	-48.51	**-179.95**	-109.1	4.70078	12.5227	7.80058	**3.34543**	3.74522
LL	64.64	66.55	28.16	**93.88**	58.45	1.55	1.539	-9E-06	**2.228**	2.028
Parameters	Gaussian copula	t-copula	Gumbel copula	Clayton copula	Frank copula	Gaussian copula	t-copula	Gumbel copula	Clayton copula	Frank copula
	China and Kazakhstan					**China and Mongolia**				
ρ	0.4153	0.4153	1.369	0.7448	2.61	-0.0318	-0.0318	1	-0.0421	-0.1963
	0.019	0.019	0.024	0.02	0.149	0.023	0.00001	0.015	0.025	0.131
DoF		6.45					3.5			
Uτ		0.45934	0.34291	0			0.40209	0.0296	0	
Lτ		0.45934	0	0.77683			0.40209	0	0.7124	
AIC	-456.4	-454.15	**-520.19**	68.4111	-430.93	-0.4398	1.64602	2.00001	**-10.263**	-0.7831
BIC	-450.6	-442.55	**-514.38**	74.2116	-425.13	5.36079	13.2472	7.80058	**-4.4623**	5.01745

LL	229.2	229.1	**261.1**	-33.21	216.5	1.22	1.177	-5E-06	**6.131**	1.392
Foreign Exchange Returns										
	China and Vietnam					**China and Turkey**				
ρ	0.02687	0.00217	1.061	-0.0501	-0.2599	0.1175	0.2111	1.099	0.3346	1.311
	0.02	0.024	0.017	0.026	0.124	0.013	0.025	0.013	0.017	0.118
DoF		8.86					4.89			
Uτ		0.56173	0.03528	0			0.60448	0.18915	0	
Lτ		0.56173	0	0.71343			0.60448	0	0.74311	
AIC	0.25567	-6.1838	**-70.223**	-19.747	-2.6733	-31.56	**-143.66**	-40.742	-4.9715	-108.1
BIC	6.05624	5.41731	**-64.422**	-13.947	3.1273	-25.76	**-132.06**	-34.942	0.82909	-102.3
LL	0.872	5.092	**36.11**	10.87	2.337	16.78	**73.83**	21.37	3.486	55.05

Parameters	Gaussian copula	t-copula	Gumbel copula	Clayton copula	Frank copula	Gaussian copula	t-copula	Gumbel copula	Clayton copula	Frank copula
	China and Dhaka					**China and Pakistan**				
ρ	0.2901	0.2818	1.238	0.4376	1.686	0.4795	0.4795	1.409	1.043	3.389
	0.018	0.022	0.021	0.022	0.121	0.014	0.014	0.021	0.028	0.148
DoF		6.8054					7.88			
Uτ		0.61051	0.23402	0			0.53604	0.42298	0	
Lτ		0.61051	0	0.7525			0.53604	0	0.79631	
AIC	-210.49	-244.75	**-305.46**	-30.153	-175.88	-630.78	-628.7	**-529.21**	-250.41	-681.35
BIC	-204.69	-233.15	**-299.66**	-24.352	-170.08	-624.98	-617.1	**-523.41**	-244.61	-675.55
LL	106.2	124.4	**153.7**	16.08	88.94	316.4	316.4	**265.6**	126.2	341.7
	China and Kazakhstan					**China and Mongolia**				
ρ	0.45	0.4501	1.303	0.8531	2.964	-0.3513	-0.3486	1	-0.1443	-2.032
	0.016	0.016	0.018	0.027	0.149	0.019	0.02	0.012	0.024	0.134
DoF		9.8					8.77			
Uτ		0.56406	0.37437	0			0.56289	0.26847	0	
Lτ		0.56406	0	0.78431			0.56289	0	0.75995	
AIC	-546.06	-544	-299.75	**-687.26**	-526.34	-316.65	**-318.49**	2.00004	-185.88	-257.81
BIC	-540.26	-532.39	-293.95	**-681.46**	-520.54	-310.85	**-306.89**	7.80061	-180.08	-252.01
LL	274	274	150.9	**344.6**	264.2	159.3	**161.2**	-2E-05	93.94	129.9

Chollete et al. (2011) claimed that using LL, AIC, or BIC to choose the best-fitted models is irrelevant for conditions when there are periods of negative dependence because copulas for negative dependence will still be chosen.

All correlation parameters r indicate positive and significant values for both stock and foreign exchange returns except for frank copula, which is insignificant for all variables. The DoF values for t-copula ranged from 3.5 to 9.8, indicating strong tail dependency and co-movements between the variables. In all pairs of stock as well as foreign exchange returns, the value of lower tail (Lt) is higher than upper tail values (Ut), which indicates that there is more dependency in lower tails (negative extremes) than the upper tails (positive extremes). Longin & Solnik (2001) proposed that when the correlation is higher on the left tail than the right tail, the bear market is the reason for increased dependence between international equity markets. Our results support their proposition. It also suggests that the dependence structure in this case is not symmetric because if symmetry exists, the difference (Ut- Lt) should be equal to zero.

The results also show that China and Vietnam (Stock index returns) and China and Pakistan (foreign exchange returns) have the highest values of upper and lower tail dependence. This indicates that their response to shock is highest compared to other markets. These results align with (those of Nguyen et al., 2022), who studied the China and Vietnam stock market dependence during the Covid-19 period and found a strong dependence of the Vietnam stock market on the Chinese stock market during that period. Similarly (Malik et al., 2018) studied the Vietnam stock market and ASEAN countries for stock market co-integration and found long-term integration effects between China and Vietnam.

Degong et al. (2023) studied the relationship between the two countries and found a long-run association between China and Pakistan's foreign exchange markets. Comparing relative copula models using LL, AIC, and BIC values, the results suggest that the Clayton copula performs better in stock returns indices, and the Gumbel copula works better for most foreign exchange returns.

Time-Varying Volatility Spillover/ Spillback Using the DCC Model

The time-varying nature of financial markets is critical since most traditional tools cannot address the time-varying nature of volatility. In this study, we used the DCC model to capture the time-varying volatility efficiently since it is essential before making an investment decision. Results of volatility spillover and spillback using the DCC model are presented in table 7. Alpha 1 shows the short-term volatility persistence, whereas beta1 shows the long-term volatility persistence of spillover effects. Persistence is calculated using the formula $\alpha 1 + \beta 1$, and the value should be less than 1 (Afzal et al., 2021). More importance is given to joint DCC $\alpha 1$ and joint DCC $\beta 1$ since they represent multivariate GARCH model, whereas parameters $\alpha 1$ and $\beta 1$ represent univariate GARCH model. Both financial markets of Vietnam and China show positive short-term and long-term spillover and spillback effects in the short and long run, except for the foreign exchange market for which joint DCC $\alpha 1$ is insignificant. However, in the long run, autocorrelation exists between the two markets. For Turkey and China, financial markets show positive short-term and long-term spillover and spillback effects in the short and long run, except for the stock exchange market, for which joint DCC $\alpha 1$ is insignificant. However, a relationship exists in the long run. The financial markets of Bangladesh and China show positive short-term and long-term spillover and spillback effects in the short term and the long run. China and Pakistan lack short-term volatility spillback effects, but in the long run, both volatility spillback effects exist in the economies' financial markets. In the case of China and Kazakhstan, short-term autocorrelation between financial markets is missing, but spillover effects exist in the long run.

Last but not least, for China and Mongolia, both effects do exist in the short and long term. To further look into the volatility spillovers and spillbacks, we plot dynamic conditional correlations between China's financial markets and other selected Countries' financial markets, as depicted in figure 6, using the DCC MGARCH model. Figure 6 reports the conditional correlations among China and other OBOR financial markets, indicating that Vietnam, Turkey, Bangladesh, Pakistan, Kazakhstan, and Mongolia markets positively correlate with China reporting time-varying conditional correlations. Figure 6 also shows the asymmetric correlations during and beyond the financial crises of Covid-19. Our results are consistent with (Batai & Chu, n.d.; Habiba et al., 2021; Hung, 2019).

Table 7 : Optimal parameters from DCC model

Index	Estimate	Std.Error	t-value	Pr(>|t|)	Index	Estimate	Std.Error	t value	Pr(>|t|)
Stock return Index									
China-Vietnam					China-Turkey				
[SSE].mu	0.0006	0.0004	1.5727	0.1158	[SSE].mu	0.0006	0.0004	1.5728	0.1158
[SSE].ar1	0.9503	0.0095	99.7062	0.0000	[SSE].ar1	0.9503	0.0095	99.6552	0.0000
[SSE].ma1	0.0872	0.0263	3.3201	0.0009	[SSE].ma1	0.0872	0.0262	3.3232	0.0009
[SSE].omega	0.0000	0.0000	0.0507	0.9595	[SSE].omega	0.0000	0.0000	0.0507	0.9596
[SSE].alpha1	0.0643	0.0116	5.5437	0.0000	[SSE].alpha1	0.0643	0.0116	5.5414	0.0000
[SSE].beta1	0.9120	0.0146	62.6224	0.0000	[SSE].beta1	0.9120	0.0146	62.5864	0.0000
[VN].mu	0.0016	0.0021	0.7631	0.4454	[XU 100].mu	0.0007	0.0005	1.4491	0.1473
[VN].ar1	0.9604	0.0371	25.8531	0.0000	[XU 100].ar1	0.9623	0.0080	119.9487	0.0000
[VN].ma1	0.0805	0.0278	2.8937	0.0038	[XU 100].ma1	0.0374	0.0188	1.9896	0.0466
[VN].omega	0.0000	0.0000	0.0709	0.9435	[XU 100].omega	0.0000	0.0000	0.1431	0.8862
[VN].alpha1	0.0655	0.0095	6.9057	0.0000	[XU 100].alpha1	0.0597	0.0148	4.0396	0.0001
[VN].beta1	0.9067	0.0120	75.5834	0.0000	[XU 100].beta1	0.9120	0.0150	60.8307	0.0000
[Joint]dcca1	0.0103	0.0035	2.9094	0.0036	[Joint]dcca1	0.0105	0.0067	1.5614	0.1184
[Joint]dccb1	0.9785	0.0081	120.5576	0.0000	[Joint]dccb1	0.9519	0.0150	63.4128	0.0000
China-Bangladesh					China-Pakistan				
[SSE].mu	0.0006	0.0004	1.5719	0.1160	[SSE].mu	0.0006	0.0004	1.5723	0.1159
[SSE].ar1	0.9503	0.0096	99.5003	0.0000	[SSE].ar1	0.9503	0.0095	99.6627	0.0000
[SSE].ma1	0.0872	0.0262	3.3258	0.0009	[SSE].ma1	0.0872	0.0262	3.3266	0.0009
[SSE].omega	0.0000	0.0000	0.0508	0.9595	[SSE].omega	0.0000	0.0000	0.0507	0.9596
[SSE].alpha1	0.0643	0.0116	5.5434	0.0000	[SSE].alpha1	0.0643	0.0116	5.5423	0.0000
[SSE].beta1	0.9120	0.0146	62.6311	0.0000	[SSE].beta1	0.9120	0.0146	62.6010	0.0000
[DSEX].mu	0.0002	0.0003	0.6728	0.5011	[KSE].mu	0.0007	0.0003	2.2630	0.0236
[DSEX].ar1	0.9691	0.0067	144.3651	0.0000	[KSE].ar1	0.9592	0.0075	127.5246	0.0000
[DSEX].ma1	0.2199	0.0251	8.7442	0.0000	[KSE].ma1	0.2021	0.0224	9.0397	0.0000
[DSEX].omega	0.0000	0.0000	0.0841	0.9330	[KSE].omega	0.0000	0.0000	0.1665	0.8677

[DSEX].alpha1	0.0500	0.0052	9.6511	0.0000	[KSE].alpha1	0.0571	0.0077	7.3689	0.0000
[Dhaka.Stock].beta1	0.9000	0.0095	95.1788	0.0000	[KSE].beta1	0.9054	0.0096	94.3782	0.0000
[Joint]dcca1	0.0058	0.0034	1.6824	0.0925	[Joint]dcca1	0.0104	0.0044	2.3927	0.0167
[Joint]dccb1	0.9844	0.0114	86.5885	0.0000	[Joint]dccb1	0.9707	0.0127	76.7239	0.0000

Index	Estimate	Std.Error	t-value	Pr(>|t|)	Index	Estimate	Std.Error	t value	Pr(>|t|)
China-Kazakhstan					China-Mongolia				
[SSE].mu	0.0006	0.0004	1.5728	0.1158	[SSE].mu	0.0006	0.0004	1.5728	0.1158
[SSE].ar1	0.9503	0.0095	99.6836	0.0000	[SSE].ar1	0.9503	0.0095	99.6851	0.0000
[SSE].ma1	0.0872	0.0262	3.3263	0.0009	[SSE].ma1	0.0872	0.0262	3.3262	0.0009
[SSE].omega	0.0000	0.0000	0.0507	0.9596	[SSE].omega	0.0000	0.0000	0.0507	0.9595
[SSE].alpha1	0.0643	0.0116	5.5425	0.0000	[SSE].alpha1	0.0643	0.0116	5.5439	0.0000
[SSE].beta1	0.9120	0.0146	62.5860	0.0000	[SSE].beta1	0.9120	0.0146	62.6294	0.0000
[KASE].mu	0.0011	0.0006	1.9736	0.0484	[MSETOP].mu	-0.0003	0.0003	-0.8319	0.4055
[KASE].ar1	0.9627	0.0081	118.4847	0.0000	[MSETOP].ar1	0.9727	0.0075	130.3249	0.0000
[KASE].ma1	0.0704	0.0260	2.7028	0.0069	[MSETOP].ma1	0.1072	0.0237	4.5231	0.0000
[KASE].omega	0.0000	0.0000	0.0930	0.9259	[MSETOP].omega	0.0000	0.0000	0.1166	0.9072
[KASE].alpha1	0.0564	0.0078	7.1836	0.0000	[MSETOP].alpha1	0.0561	0.0093	6.0591	0.0000
[KASE].beta1	0.9075	0.0127	71.7268	0.0000	[MSETOP].beta1	0.9083	0.0123	73.9982	0.0000
[Joint]dcca1	0.0053	0.0023	2.3180	0.0204	[Joint]dcca1	0.0113	0.0054	2.0851	0.0371
[Joint]dccb1	0.9897	0.0045	221.2027	0.0000	[Joint]dccb1	0.9605	0.0096	99.9030	0.0000
Foreign exchange returns									
China-Vietnam					China-Turkey				
Index	Estimate	Std.Error	t value	Pr(>|t|)	Index	Estimate	Std. Error	t value	Pr(>|t|)
[USD_CYN].mu	0.0000	0.0001	0.4228	0.6725	[USD_CYN].mu	0.0000	0.0001	0.4229	0.6724
[USD_CYN].ar1	0.9713	0.0138	70.6374	0.0000	[USD_CYN].ar1	0.9713	0.0138	70.5977	0.0000
[USD_CYN].ma1	-0.0149	0.0383	-0.3881	0.6979	[USD_CYN].ma1	-0.0149	0.0383	-0.3887	0.6975
[USD_CYN].omega	0.0000	0.0000	0.0007	0.9995	[USD_CYN].omega	0.0000	0.0000	0.0007	0.9995
[USD_CYN].alpha1	0.0500	0.0289	1.7330	0.0831	[USD_CYN].alpha1	0.0500	0.0289	1.7330	0.0831
[USD_CYN].beta1	0.9000	0.0599	15.0249	0.0000	[USD_CYN].beta1	0.9000	0.0599	15.0252	0.0000
[USD_VDN].mu	0.0001	0.0001	0.9068	0.3645	[USD_TRY].mu	0.0005	0.0002	2.9463	0.0032
[USD_VDN].ar1	0.9837	0.0145	67.8917	0.0000	[USD_TRY].ar1	0.9302	0.0183	50.7743	0.0000

[USD_VDN].ma1	-0.0163	0.0462	-0.3524	0.7245	[USD_TRY].ma1	0.1466	0.0345	4.2555	0.0000
[USD_VDN].omega	0.0000	0.0000	0.0007	0.9995	[USD_TRY].omega	0.0000	0.0000	0.0096	0.9924
[USD_VDN].alpha1	0.0500	0.0055	9.0278	0.0000	[USD_TRY].alpha1	0.0966	0.0168	5.7547	0.0000
[USD_VDN].beta1	0.9000	0.0131	68.8239	0.0000	[USD_TRY].beta1	0.8935	0.0166	53.6853	0.0000
[Joint]dcca1	0.0000	0.0001	0.0002	0.9999	[Joint]dcca1	0.0038	0.0022	1.7285	0.0839
[Joint]dccb1	0.9456	0.1070	8.8394	0.0000	[Joint]dccb1	0.9902	0.0052	189.5823	0.0000

Index	Estimate	Std.Error	t-value	Pr(>|t|)	Index	Estimate	Std.Error	t value	Pr(>|t|)
China-Bangladesh					China-Pakistan				
Index	Estimate	Std.Error	t value	Pr(>|t|)	Index	Estimate	Std.Error	t value	Pr(>|t|)
[USD_CYN].mu	0.0000	0.0001	0.4229	0.6724	[USD_CYN].mu	0.0000	0.0001	0.4225	0.6727
[USD_CYN].ar1	0.9713	0.0138	70.6308	0.0000	[USD_CYN].ar1	0.9713	0.0138	70.6164	0.0000
[USD_CYN].ma1	-0.0149	0.0383	-0.3883	0.6978	[USD_CYN].ma1	-0.0149	0.0384	-0.3878	0.6982
[USD_CYN].omega	0.0000	0.0000	0.0007	0.9995	[USD_CYN].omega	0.0000	0.0000	0.0007	0.9995
[USD_CYN].alpha1	0.0500	0.0289	1.7331	0.0831	[USD_CYN].alpha1	0.0500	0.0289	1.7330	0.0831
[USD_CYN].beta1	0.9000	0.0599	15.0255	0.0000	[USD_CYN].beta1	0.9000	0.0599	15.0243	0.0000
[USD_BDT].mu	0.0001	0.0002	0.7168	0.4735	[USD_PKR].mu	0.0003	0.0035	0.0978	0.9221
[USD_BDT].ar1	0.9489	0.0317	29.8877	0.0000	[USD_PKR].ar1	0.9601	0.2479	3.8736	0.0001
[USD_BDT].ma1	-0.3009	0.2958	-1.0171	0.3091	[USD_PKR].ma1	0.0389	0.0521	0.7465	0.4554
[USD_BDT].omega	0.0000	0.0000	0.0012	0.9991	[USD_PKR].omega	0.0000	0.0000	0.0002	0.9998
[USD_BDT].alpha1	0.0500	0.0093	5.3827	0.0000	[USD_PKR].alpha1	0.0500	0.0550	0.9090	0.3633
[USD_BDT].beta1	0.9000	0.0023	396.9861	0.0000	[USD_PKR].beta1	0.9000	0.1939	4.6405	0.0000
[Joint]dcca1	0.0058	0.0023	2.5493	0.0108	[Joint]dcca1	0.0031	0.0053	0.5831	0.5598
[Joint]dccb1	0.9807	0.0067	146.4958	0.0000	[Joint]dccb1	0.9549	0.0667	14.3085	0.0000
China-Kazakhstan					China-Mongolia				
Index	Estimate	Std.Error	t value	Pr(>|t|)	Index	Estimate	Std.Error	t value	Pr(>|t|)
[USD_CYN].mu	0.0000	0.0001	0.4235	0.6720	[USD_CYN].mu	0.0000	0.0001	0.4228	0.6725
[USD_CYN].ar1	0.9713	0.0138	70.6356	0.0000	[USD_CYN].ar1	0.9713	0.0138	70.6402	0.0000
[USD_CYN].ma1	-0.0149	0.0383	-0.3881	0.6979	[USD_CYN].ma1	-0.0149	0.0383	-0.3881	0.6980
[USD_CYN].omega	0.0000	0.0000	0.0007	0.9995	[USD_CYN].omega	0.0000	0.0000	0.0007	0.9995
[USD_CYN].alpha1	0.0500	0.0288	1.7335	0.0830	[USD_CYN].alpha1	0.0500	0.0289	1.7330	0.0831
[USD_CYN].beta1	0.9000	0.0599	15.0299	0.0000	[USD_CYN].beta1	0.9000	0.0599	15.0249	0.0000
[USD_KZT].mu	0.0000	0.0001	-0.1183	0.9059	[USD_MNT].mu	0.0004	0.0003	1.1768	0.2393
[USD_KZT].ar1	0.9571	0.0159	60.1831	0.0000	[USD_MNT].ar1	0.9702	0.0182	53.1705	0.0000
[USD_KZT].ma1	0.1640	0.0521	3.1459	0.0017	[USD_MNT].ma1	-0.0780	0.0356	-2.1891	0.0286
[USD_KZT].omega	0.0000	0.0000	0.0027	0.9979	[USD_MNT].omega	0.0000	0.0000	0.0023	0.9982
[USD_KZT].alpha1	0.0587	0.0185	3.1816	0.0015	[USD_MNT].alpha1	0.0500	0.0164	3.0555	0.0022
[USD_KZT].beta1	0.9282	0.0150	61.8147	0.0000	[USD_MNT].beta1	0.9000	0.0354	25.3971	0.0000
[Joint]dcca1	0.0059	0.0044	1.3506	0.1768	[Joint]dcca1	0.0037	0.0017	2.1842	0.0289
[Joint]dccb1	0.9917	0.0034	295.0984	0.0000	[Joint]dccb1	0.9919	0.0034	289.1572	0.0000

Conclusion

Analysis of financial market risk and evaluating volatility spillover is crucial in making investment decisions. Investors need to look into the behaviors specially when investing in international portfolios to look into the dependences of financial markets to save them from financial losses. One Belt One Road (OBOR) is an international cooperation program initiated by Xi Jinping (Chinese president) in 2013, aiming at the creation of economic trade, promoting regional cooperation, and enhancing the effectiveness of regional markets. OBOR covers more than 70 countries (2/3 of the world's population) and approximately a third of the world's GDP (Du & Zhang, 2018). The purpose of this study is to investigate the correlations, volatility spillover, and spillback between China and OBOR initiative countries to measure the time-varying behavior in the financial markets. Two financial markets i.e. the stock market and the foreign exchange were selected for the study. Out of the 19 countries that directly made part of the corridor, 6x countries (each representative of one corridor) having maximum trade based on their balance of trade values were selected for this study. So, data for this study was collected from six major trading countries (Vietnam, Turkey, Bangladesh, Pakistan, Kazakhstan, and Mongolia) from OBOR countries and their relationship will be studied with China. The daily closing prices of stocks and exchange rates were taken. The data was collected from 1st January 2013 to 31st December 2022. DCC M GARCH model along with copula was applied for the analysis of this study. R programming is used for data analysis using R-studio. All sample financial markets showed an asymmetric Dependence on Chinese financial markets and this dependence increases during times of financial crises or shock periods as compared to good times. All financial markets also indicated two-way time-varying volatility spillover effects in the long run. The financial crises may further intensify these spillover effects.

The study helps investors and policy makers when making decisions regarding international portfolio investments. This study will also give future directions to study time varying market behaviors to estimate risk and develop innovative risk measuring techniques.

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Appendix

Table 7: Representative country of each corridor

Ser	Countries	Corridor Name	Stock exchange	Currency
1	Vietnam	China-Indochina Peninsula Economic Corridor	Vietnam stock market (VNINDEX Index)	Dong
2	Turkey	China-Central Asia-West Asia Economic Corridor	BIST stock exchange (XU100 Index)	Lira
3	Bangladesh	Bangladesh-China-India-Myanmar Economic Corridor	Dhaka stock exchange (DSEX Index)	Taka
4	Pakistan	China-Pakistan Economic Corridor	Pakistan stock exchange (KSE100 Index)	Rupee
5	Kazakhstan	New Eurasia Land Bridge Economic Corridor, China-Central Asia-West Asia Economic Corridor	Kazakhstan stock exchange (KASE Index)	Kazakhstani Tenge
6	Mongolia	China-Mongolia-Russia Economic Corridor	Mongolia stock exchange (MSETOP Index)	Mongolian Tugrik

Figure: 3 Price Movements of OBOR related to China Stock and Foreign Exchange market

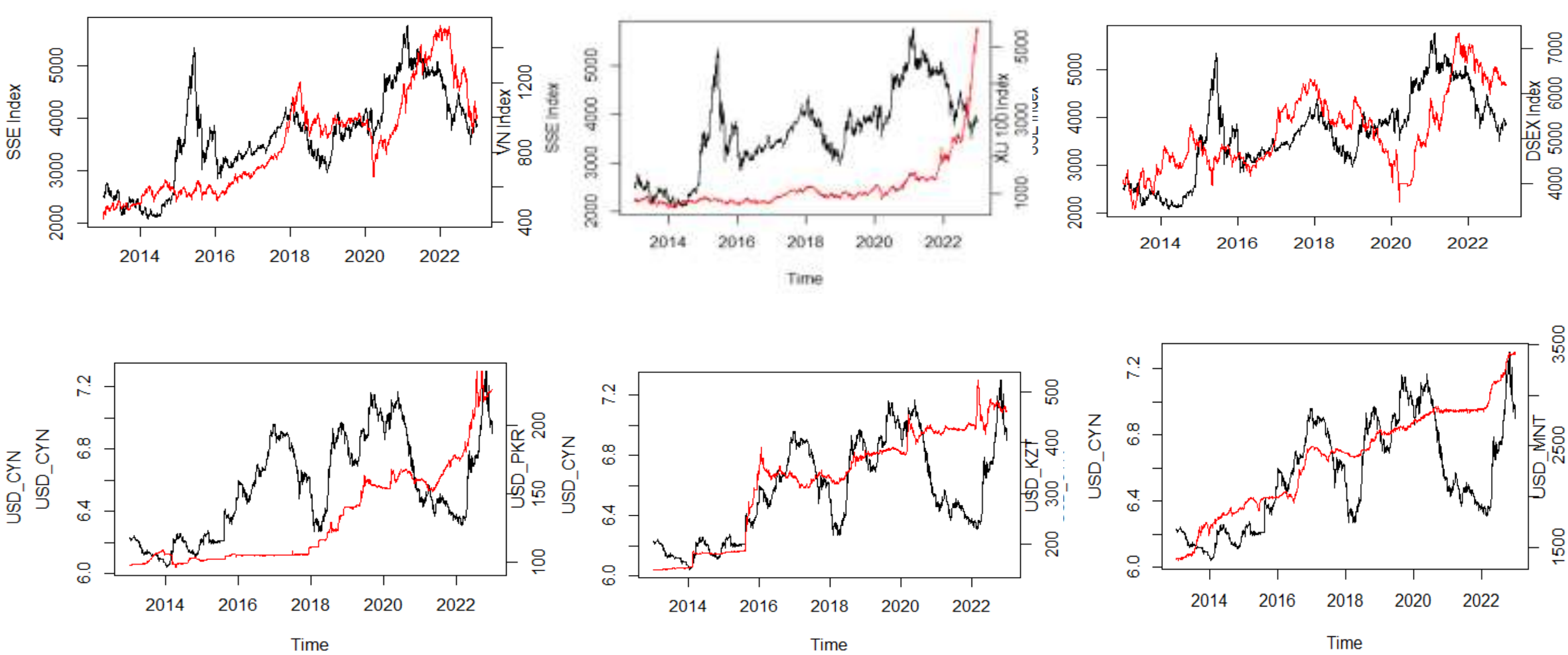

Figure: 4 Q-Q plots showing non - normal distribution

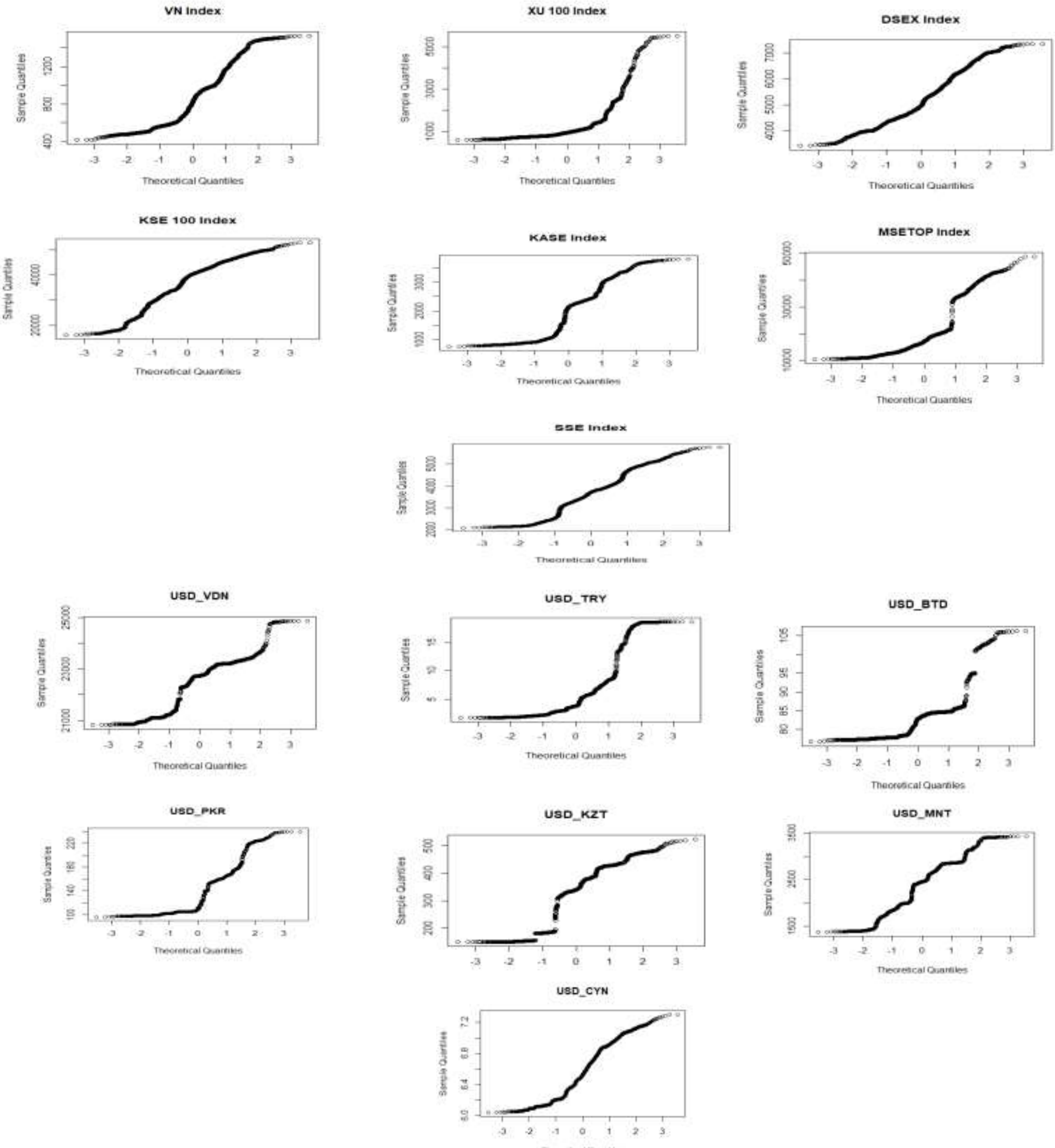

Figure: 5 Q-Q plots showing normal distribution

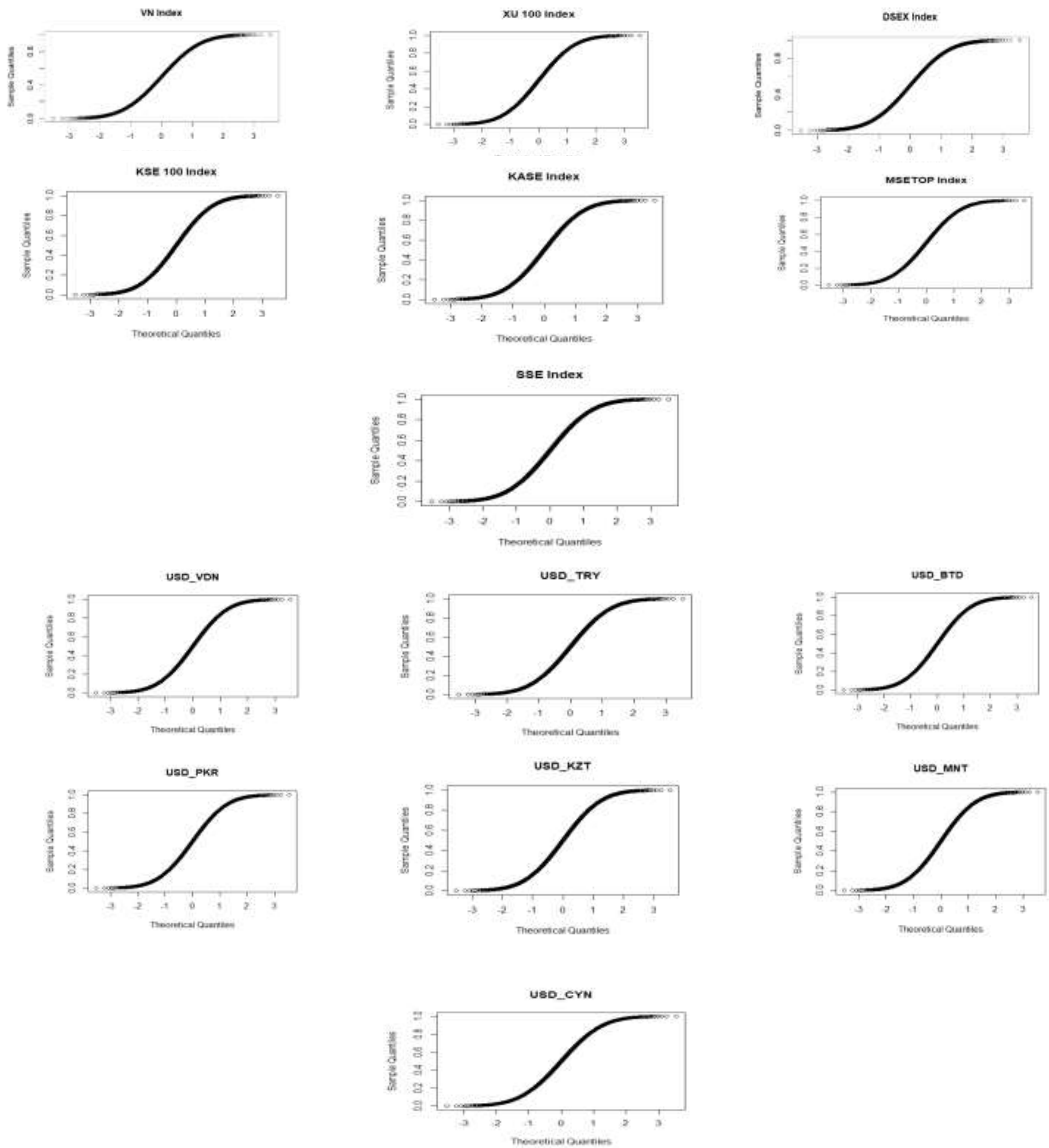

Figure: 6 Dynamic conditional correlation between China and OBOR financial markets