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Analyzing Markov dependence-switching between E7 stock markets

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ABSTRACT

We investigate the dependence structure among the seven emerging stock markets namely Brazil, China, India, Indonesia, Mexico, South Korea, and Turkey for the period 2000 to 2018 by employing a dependence-switching copula model. This model allows us to investigate the tail dependence and regime shift between positive and negative correlation for bull and bear stock pairs. Our overall results show that under the negative correlation regime, only 8 out of 21 paired stock markets have asymmetric dependence, and 6 out of 21 paired stock markets have asymmetric tail dependence. Although the emerging stock markets are deemed by the global investors to be a homogenous class, these stock markets manifest varied degree of traits. Henceforth, from a portfolio diversification perspective, the global investors can exploit the diversification opportunities offered by the selected stock markets. These findings have appropriate implications from the perspective of asset pricing and risk management. The study recommends that regulators should provide a road-map for identifying risk's effects across the selected emerging stock markets. Moreover, policy makers should consider what further financial collaboration they intend to pursue for enabling greater accessibility to the selected emerging stock markets.

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1. Introduction

Dependence structure of stock markets has been acknowledged as a central theme on the landscape of portfolio management. Grubel (1968) highlighted the canons of Markowitz (1952) and reported that the diversified portfolio at the international level generates a better proportion of returns and lower variances in comparison with the diversification of assets at the domestic level. This statement is supported by Levy and Sarnat (1970), Agmon (1972), and Grauer and Hakansson (1987). Portfolio risk

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decreases because of proper diversification of funds in the worldwide equity markets that have low correlation. This enthusiasm leads to the investigation of the dependence and tail dependence framework among the worldwide stock markets in pursuit for those markets exhibiting low linkages. Studies have revealed that incorporating the emerging markets to a developed market equity portfolio will be valuable for effective portfolio diversification (Ajayi & Mehdian, 1995; Bowman & Comer, 2000). In the last few decades, emerging economies have garnered attention on account of economic accomplishment. On account of better returns, the emerging markets have unfolded as a center of attraction for the diversified portfolio at the international level. Thus, multiple studies highlight the worth of incorporating emerging stock markets in the developed market portfolios as it promotes the proper spreading of investments and assists the international stakeholders in attaining higher gains (Barry, Peavy, & Rodriguez, 1998; Buchanan, English, & Gordon, 2011).

Emerging markets are characterized with a group of economies having promising stock markets, which have unlocked the landscape of local financial markets to the global investors through the following modes: openness to foreign ownership, ease of capital inflows/outflows, enhancing the competence of the operational framework, and strengthening the stability of institutional framework (The Economist, 2020). The ambit of emerging markets has magnified to include economies from Asia, Africa, to South America. Moreover, the emergence of E7 emerging markets as a powerful economic bloc illustrates a paradigm shift on the landscape of the global economy. The current study focuses on seven emerging stock markets, namely, Brazil, China, India, Indonesia, Mexico, South Korea, and Turkey.[1] These markets are rapidly growing owing to diminishing state regulations and the private drivers' significant partaking. The purported emerging economies are members of global economic organizations, thereby are highly linked up to the international economic landscape in connection with trade, investment, and market interdependence. These emerging markets are instrumental in accelerating the future growth of international trade and financial solidity (Mensi et al., 2016; Kearney, 2012; Laopodis & Papastamou, 2016; Nielsen, Hannibal, & Larsen, 2018).

The world stock markets have grown considerably over the past three decades, with emerging markets significantly contributing to this expansion. The bulk of emerging economies' domestic financial liberalization policies have put a significant emphasis on stock market development (Yartey, 2008). About 80% of the output of all emerging markets is produced by the seven selected emerging market economies. Similar to the G7 (the Group of Seven major developed countries), this club, recognized as E7, has equally been the primary driver of growth in emerging markets and their integration into the world economy (Huidrom et al, 2020). Understanding dependence structure among the E7 has grown more crucial given the changing economic landscape. The limited amount of research pertaining to E7 stock markets tends to motivate this work.

We identified these economies because their stock market brings diversification and the opportunity for risk-adjusted returns. Because of their continuous reforms and incorporation into the global financial environment, global investors have acknowledged emerging stock market. While the stock market of these markets provides gains, they also expose global investors to the dynamics of these stock market dependence structures. Thus, investigating and revealing the interconnections between these markets is relevant.

Notwithstanding the useful contributions made in the research area of linkages among the stock markets, the critical question is to gauge the dependence framework among the emerging markets. The routes of dependence between the paired stock markets are made on account of a positive (portfolio rebalancing) or negative correlation (return chasing effect). Portfolio rebalancing gives investors the opportunity to recoup gains from the domestic markets and reinvest in other growing markets offering better prospects. Correspondingly, this causes a positive correlation between the stock markets (Hau & Rey, 2004). By contrast, in return chasing, negative links between the stock markets is revealed. The global investors compete to procure when the local market is advancing and make an exit in a plunging domestic market. The return-chasing behavior of international investors in the emerging stock markets is well endorsed (Kim & Wei, 2002; Chai-Anant & Ho 2008). Studies have reported that the correlation coefficient cannot measure the asymmetric dependence relationships between asset returns (Blyth, 1996; Shaw, 1997). Likewise, the DCC-GARCH and regime-switching models have pitfalls in capturing asymmetric dependence (Boubaker & Sghaier, 2014).

The copula is rank-based and is invariant to increasing and continuous transformations. Patton (2006) brought the time-varying copulas to accommodate time variation in the dependence structure. This present study encompasses Patton's (2006) expansion of Sklar's (1959) theorem for conditional distributions and the parametric model on the unfolding of the copula.

A study of dependence framework between the paired emerging stock market through the copula is a robust approach in terms of portfolio and risk management. It shall guide the investors to apportion their fund in a well-thought-out manner, especially in handling probable extreme losses that can happen concurrently in other selected emerging equity indices.

With this in perspective, we make two contributions to the extant literature; our investigation is indeed the first in domain of emerging stock markets employing a dependence-switching copula approach to explore the dependence structure between the selected emerging stock markets. We illustrate how the correlation between paired emerging stock markets shifts between positive and negative correlation regimes depending on whether the return chasing or portfolio rebalancing effect is dominant. Second, our results provide more insights into asset allocation decisions in the seven emerging countries, enabling global investors to better understand the mechanism of dependence structure across these countries.

Studies manifesting the relation among the emerging markets are plentiful, but those investigating the dependence structure among the emerging stock markets through the copula methodology are sparse. As a result, this research aims to fill a vacuum in the literature by presenting fresh empirical evidence on the dependence structure of seven emerging stock markets, namely, Brazil, China, India, Indonesia, Mexico, South Korea, and Turkey.

Thus, following Wang, Wu, and Lai (2013), our work measures the time-varying dependence switching copula in selected emerging markets. The present study proposes the conditional correlations between the paired stock markets to switch between the negative and positive regimes, conditional to whether the forces of portfolio rebalancing and return chasing are prevailing. Moreover, the time-varying dependence switching copula is utilized to study the dependence framework in selected emerging markets. The rationale of employing this tool is, primarily, the combination of Clayton copula with the survival Clayton copula, covers asymmetric tail dependence. In addition, this study sets the dependence structure between the stock markets to oscillate between the positive and negative correlation settings that mimic the existent sphere where the dependence can fluctuate. Lastly, this study gauges the tail dependence structure through the following stock market settings: (a) bear-bull stock markets; (b) bull-bear stock markets; (c) bear-bear stock markets; and (d) bull– bull stock markets.

Our empirical results report that in a negative correlation regime, when one booming stock market associates with a crashing stock market, the left and tail dependence are significant for 8 out of 21 and 6 out of 21 paired stock markets, respectively, at the conventional levels. However, in the case of positive correlation regime, when both purported markets are booming and crashing, the right and tail dependence are significant for 8 out of 21 paired stock markets and none, respectively, at the conventional levels. Our results exhibit that under the negative correlation regime, symmetric centric dependence and symmetric centric tail dependence occurred in most of the paired stock markets. Accordingly, under the positive correlation regime, symmetric dependence occurred in considerable cases of paired stock markets, whereas symmetric tail dependence is present in totality for all the covered markets. These findings have appropriate implications from the perspective of asset pricing and risk management.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 covers the methodology. Section 4 incorporates the data and unfolds the empirical outcomes. Section 5 covers conclusion and policy implications.

2. Literature review

Several scholars have employed various methods of data analysis on the dependence structure of equity markets: correlation and conditional correlations (Forbes & Rigobon, 2002), DCC multivariate GARCH model (Sedik & Williams, 2011), ARMA-EGARCH model (Kim et al., 2005), rolling bi-correlation tests (Lim et al., 2008), regime switching models (Guo et al., 2011), co-integration analysis (Arouri et al., 2011), multiple regression (Alam & Hussein, 2019), VECM method (Alam et al., 2020), wavelet analysis (Rua & Nunes, 2009), multivariate VAR framework (Wang, 2014), and vector autoregression technique (Elyasiani, 1998). Thus, several scholars have used a range of data techniques to investigate the dynamic linkages of equities markets through an appropriate model covering specific distribution.

These are the fundamental concepts for econometric models, but it is revealed that it is challenging for examining the asymmetry in the tail dependence through above cited methods. For the purpose of capturing nonlinear dependence, copula functions have been developed. In enhanced financial modeling, copulas are employed to explain data with skewness and fat tails. An important method for identifying nonlinear dependence between asset returns is copula functions.

Copulas split the dependence framework from the marginal distributions and permit significant flexibility in the system of a suitable multivariate distribution for returns. Multiple works substantiated the copula-based studies of dependence structure. The purported studies elucidated the strong indication of asymmetric dependence in the joint distribution function of a set of random variables. Copulas demonstrate the superiority in modeling the dependence in populations with asymmetrical tails and provide enhanced attention into relationships among the selected variables. Multiple studies have utilized the copula approach for the developed stock markets (Jondeau & Rockinger, 2006; Peng & Ng, 2012; Kakouris & Rustem, 2014). Several others investigated the emerging economies (Rodriguez, 2007; Ning & Wirjanto, 2009) and examined the linkage between the developed and emerging markets (Wang et al., 2011; Ye et al., 2012).

For instance, utilizing two different dependence measures, correlations, and copulas, Chollete et al. (2011) investigated diversification opportunities in international markets. They uncovered that the conflict on which countries have the largest and smallest diversification gains is revealed by dependence measures. Moreover, Okimoto (2008) revealed asymmetric dependence structures on the landscape of international equity markets by employing the Markov switching model in tandem with copula theory. Rodriguez (2007) unearthed that the dependence arrangement between stock market returns of Asian and Latin American countries were affected during the turmoil. Kenourgios et al. (2007) revealed an asymmetrical intensification in dependence among Brazil, Russia, India, and China (BRIC) and the two developed US and UK markets during the recent financial crises through the application of multivariate copula regime-switching approach. Furthermore, Bartram et al. (2007) uncovered through a time-varying copula model that the market dependence for bigwig equity markets has intensified within the Euro sphere with the embarking of Euro. Meanwhile, Aloui et al. (2011) through copula exhibit strong indication of time-varying evidence between the BRIC and US markets. Boubaker and Sghaier (2014) also applied time-varying copula functions and revealed symmetric dependence between the American and Japanese stock markets and asymmetric dependence between the American and European stock markets. Mensah and Alagidede (2017) revealed that the dependence is time variant and asymmetrical in nature. Further, there was no spillover influence on African emerging markets because of the extreme sinking of price movement in the advanced market.

Employing the copula, Basher, Nechi, and Zhu (2014) examined six gulf economies and revealed that conditional dependence throughout the 21 pairs of equity stock returns is not straightly symmetrical. The lower tail dependence is markedly larger than the upper tail dependence. Ning and Wirjanto (2009) through the copula method manifested substantial and asymmetrical return volume reliance at the extremes for the six emerging East Asian equity markets. Using dependence-switching copula model, Wang et al. (2013) disclosed that the dependence and tail dependence associating to the stock and foreign exchange markets are asymmetric (symmetric) for a good number of countries in the negative (positive) correlation period. Ning (2009) examined the dependence framework through a mixture copula model, which exhibited noteworthy asymmetric tail dependence in the majority of return paired, with lower tail dependence being greater than the upper tail dependence. Likewise, the dependence is time variant and in sync toward the integration in European and East Asian markets excluding North American markets. Further, the dependence is more intracontinental than intercontinental. By means of time-varying copulas, Boubaker and Raza (2016) brought to fore considerable evidence of co-movement between the US and CEE equity markets and revealed that the co-movement exhibits sizeable time variations and unevenness in the tails of the return distributions. Yang and Hamori (2013) revealed existence of an asymmetric dependence linkage between developed and emerging markets. Additionally, multiple studies through copula reveals asymmetric dependence among the stock markets (Yang et al., 2015; Okimoto,2014; Mokni & Mansouri,2017; Hussain & Li, 2018).

3. Methodology

3.1. Copula specification

The copula is a robust tool to gauge the nonlinear dependence between variables. This method can capture different types of dependence throughout the entire distribution of asset returns. The copula modeling is well acknowledged, and the illustrations of its application in finance are numerous. There are multiple advantages in applying copulas in measuring the financial markets co-movement. Primarily, copulas encompass both the linear and nonlinear dependence of the variables. At a given time, copula serves two-fold. First, it draws out the dependence structure both from the joint distribution function and from the marginal behavior. The copula model incorporates the degree and the structure of the dependence. Second, it captures the tail dependence and asymmetric dependence. In connection, this study works out on a dependence-switching copula.[2]

The employment of copula functions, the marginal models, and the estimation procedure manifest the dependencies among the purported stock markets. Copulas stipulate a suitable method to demonstrate the joint distributions of random variables with superior flexibility both in marginal distributions and dependence structure. Centered on Sklar's (1959) theorem, the joint distribution of two random variables can be explained through a copula, once the transformation of marginal distributions into uniform distributions is completed. This study concentrates on the dependence framework between two stock market returns (X_1 and X_2). Consequently, a bivariate joint cumulative distribution (F) of the two stock market returns (X_1, t) and (X_2, t) can be separated into two marginal cumulative distribution functions (F_1 and F_2), and a copula cumulative distribution function (C) provides the dependence framework between the two purported series. In line, the variables' joint distribution can be illustrated through a copula function C represented as

$$F\left(X_{1,t},\ X_{2,t};\ \delta_1, \delta_{2;}\ \theta^c\right) = C\left(F_1(X_{1,t},\ \delta_1),\ F_2\left(X_{2,t},\ \delta_2\right); \theta^c\right), \tag{1}$$

where $F_K(X_{K,t};\ \delta_K)$, $K=1,\ 2$, is the marginal cumulative distribution function of $X_{K,t}$ and δ_K, whereas θ^c is the parameter set of $F_K(X_{K,t};\ \delta_K)$ and C.

Considering that all the cumulative distribution functions are differentiable, we can express the bivariate joint density as

$$f\left(X_{1,t},\ X_{2,t};\ \delta_1, \delta_{2;}\ \theta^c\right) = c\left(u_{1,t},\ u_{2,t};\ \theta^c\right) \prod_{K=1}^{2} f_k(X_{k,t};\ \delta_k), \tag{2}$$

where $f\left(X_{1,t}, X_{2,t}; \delta_1, \delta_{2;}\theta^c\right) = \partial F^2\left(X_{1,t}, X_{2,t}; \delta_1, \delta_{2;}\theta^c\right)/\partial X_{1,t}\partial X_{2,t}$ is the joint density of $X_{1,t}$ and $X_{2,t}$. $u_{k,t}$ is the probability integral transformation of $X_{K,t}$ based on

$F_K(X_{K,t};\delta_K)$, K = 1, 2; $C(u_{1,t},u_{2,t};\theta^c) = \partial C^2(u_{1,t}-u_{2,t},\theta^c) = {}^{\partial C^2(u_{1,t},u_{2,t};\theta^c)}\Big/_{\partial}u_{1,t}\partial u_{2,t}$ is the copula density function; and $F_K(X_{K,t};\ \delta_K)$ is the marginal density of $X_{k,t}$, where K = 1, 2. The bivariate joint density of $X_{1,t}$, and $X_{2,t}$ is the outcome of the copula density and the two marginal densities.

As described above, the linkage between the stock markets can be positive (return-chasing effect) or negative (portfolio-rebalancing effect) that relies on the forte of two distinctive effects. If the former effect is more prevalent for some time periods and the latter effect leads for the other time phases, then the co-movement amid the stock markets clocks between positive and negative regimes. In order to obtain the dependence switching, we employ a Markov switching copula approach, in which the unobserved state variable affects the copula function and marginal models (Wang et al., 2013, 2018).

We consider the following state-varying copula:

$$C_{S,t}\left(u_{1,t},\ u_{2,t};\ \theta_1^C\theta_0^C\right) = \begin{cases} C_1\left(u_{1,t},\ u_{2,t};\ \theta_1^C\right),\ if\ S_t = 1 \\ C_0\left(u_{1,t},\ u_{2,t};\ \theta_0^C\right),\ if\ S_t = 0 \end{cases}$$

where S_t is an unobserved state variable. Correspondingly, $C_1\left(u_{1,t},\ u_{2,t};\ \theta_1^C\right)$ and $C_0\left(u_{1,t},\ u_{2,t};\ \theta_0^C\right)$ are the two blended copulas with positive and negative dependence structures, respectively. The above-mentioned copula function mixes the Clayton copula (C^c) with the survival Clayton copula (C^{SC}).[3]

$$C_1\left(u_{1,t},\ u_{2,t};\ \theta_1^C\right) = C^C(u_{1,t},\ u_{2,t};\ \alpha_1) + C^{SC}(u_{1,t},\ u_{2,t};\ \alpha_2), \tag{3}$$

$$C_0\left(u_{1,t},\ u_{2,t};\ \theta_0^C\right) = C^C(1-u_{1,t},\ u_{2,t};\ \alpha_3) + C^{SC}(1-u_{1,t},\ u_{2,t};\ \alpha_4), \tag{4}$$

where $\theta_1^C = (\alpha_1,\alpha_2)'$, $\theta_0^C = (\alpha_3,\alpha_4)'$; $C^C(u,\upsilon,\alpha) = (u^{-\alpha}+\upsilon^{-\alpha}-1)^{-1/\alpha}$, $C^{SC}(u,\upsilon,\alpha) = (u+v-1)+C^c(1-u,\ 1-\upsilon,\alpha)$ and $\alpha\in(0,\ \infty)$. After the estimation of the shape parameter, α_1, it can be changed in order to obtain Kendall's τ_i, correlation coefficient ρ_1, and tail dependence φ_i with $\tau_i = {}^{\propto_i}/_{(2+\propto_i)}$, $\rho_1 = \sin(\pi*\tau_i/2)$ and $\varphi_i = 0.5*2^{-1/\propto_i}$, for i = 1, 2, 3, 4.

ρ_2 (ρ_3) and ρ_1 (ρ_4) compute the dependence of the high and low returns, respectively, between the stock markets. They are the dependence measures computed under the normal stock market conditions. In line, $\varphi_2(\varphi_3)$ and $\varphi_1(\varphi_4)$ gauge the dependence of extremely high and extremely low returns, respectively, between the stock markets. They are computed under the extreme stock market conditions. The unobserved state variable S_t follows the standard of Markov switching chain with a transition probability matrix represented as follows:

$$p = \begin{bmatrix} p_{00} & 1-p_{00} \\ 1-p_{11} & p_{11} \end{bmatrix}$$

where $p_{ij} = 1-p_{11}\Pr[S_t = j|S_{t-1} = i|]$ for I, j = 0, 1.

The state variable S_t moves amid the negative and the positive dependence regimes.

The bivariate density function of the just mentioned model is stated as

$$f\left(\eta_1, \eta_{2,} \delta_1^1, \delta_1^0, \ \delta_2^1, \ \delta_2^0, \ \theta_c^1, \ \theta_c^0\right) = \left\{\sum_{j=0}^{1} \Pr(S_t = j) C^j\left(u_{1,t}, \ u_{2,t}; \ \theta_c^j\right) \prod_{k=1}^{2} \left\{\sum_{j=0}^{1} \Pr(S_t = j) f_k\left(\eta_k, \ \delta_k^j, \ S_t = j\right)\right\}\right\} \tag{5}$$

Processing equation 5 into log-likelihood is exhibited in the following mode:

$$L(\vartheta) = \ L_c(\varphi_1) + \ \sum\nolimits_{K=1}^{2} L_k(\varphi_{2,k}), \tag{6}$$

where $\vartheta = \left(\theta_c^1, \ \theta_c^0, \ \delta_1^1, \delta_1^0, \ \delta_2^1, \ \delta_2^0, \ p_{11}, \ p_{00}\right); \ L_c(\varphi_1)$ and $L_k(\varphi_{2,k})$ are the log of the copula density and the marginal density of X_k, respectively. These densities are stated as follows:

$$L_c(\varphi_1) = \log\left[\Pr(S_t = 1) c^1(u_1, \ u_2; \ \theta_c^1) + \left(1 - \Pr(S_t = 1) c^0(u_1, \ u_2; \ \theta_c^0)\right)\right],$$

$$L_K(\varphi_{2,k}) = \log[\Pr(S_t = 1) f_k(\eta_k : \delta_k^1. \ S_t = 1) + \left(1 - \Pr(S_t = 1) f_k(\eta_k, \delta_k^0. \ S_t = 0)\right)]$$

where $\varphi_1 = (\theta_c^1, \ \theta_c^0, \ p_{11}, \ p_{00})$.

3.2. Marginal models

Using skewed t-distribution, we frame work the log-return time-series by applying the GJR-GARCH(p, q) format of Glosten, Jagannathan, and Runkle (1993). We consider the ensuing returns series:

$$r_t = \phi + \epsilon_t,$$

where ϕ is the expected return and ϵ_t is a zero mean white noise term. Notably, this paper states that $\epsilon_t \sim GJR - GARCH$ if we can pen $\epsilon_t = \sigma_t z_t$, where z_t is standard Gaussian and (in more generalized mode to justify for more lags).

$$\sigma_t^2 = \omega + \sum\nolimits_{i=1}^{q} \left(\alpha_i \epsilon_{t-\mathrm{i}}^2 + \gamma_i I_{t-i} \epsilon_{t-i}^2\right) + \sum\nolimits_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{7}$$

where ω is a constant, ϵ_{t-i} is the ARCH component, σ_{t-j}^2 is the GARCH component, and

$$I_{t-i} = \begin{cases} 0 \ \ if, \ \ r_{t-1} \geq \phi \\ 1 \ \ if, \ \ r_{t-1} < \phi \end{cases}.$$

The number of lags (p, q) is chosen in line with the Akaike information criteria (AIC).

3.3. Estimation methodology (available in supplementary materials)

4. Empirical investigation

4.1. Data description

In this study, daily data of stock market indices from January 1, 2000, to October 2018 are extracted from the Bloomberg database covering 4,998 observations. The countries under consideration are Brazil, China, India, Indonesia, Mexico, South Korea, and Turkey. Table S1 presents the descriptive statistics for the data series. The average stock indices returns for the selected countries except Turkey are similar, and the corresponding standard deviation reveals related attributes. All the stock market indices returns series exhibit excess kurtosis and are rejected following a normal distribution substantiated by Jarque–Bera normality test.

4.2. Parameter estimates for the marginal distribution models

A marginal model's best specification is essential to prevent biased copula estimations. Table S2 conveys the estimation results of the AR(1)-SPLINE-GJR model for the purported indices. Multiple diagnostic tests are fitted to test the hypotheses of no serial correlation and autoregressive conditional heteroscedasticity in the estimated residuals. The test statistics cover the Q-statistic, the Q2-statistic, and the ARCH-LM statistic. The Ljung–Box tests for serial correlation in the standardized residuals (the Q (10) statistic) and squared standardized residuals (the Q2(10) statistic) accept the null hypothesis of no autocorrelation, with a few exceptions. Similarly, the ARCH LM statistics accept the null hypothesis of no remaining ARCH effects in the estimated residuals. The purported tests fail to reject the hypothesis at the standard levels. In sum, the results reveal that the marginal models are well fitted by the AR(1)-SPLINE-GJR models. It is essential to report the well-specified models to make sure that the estimated copula model suitably obtains the dependence structure of the purported indices.

4.3. Estimation of the Copula models

In estimating the dependence-switching copula model, first, we calculate a number of single-copula models, namely, the Gaussian copula, student-t copula, and four distinct forms of the Clayton copula. Table S3 encompasses the parameters estimate of the single-copula models. To gauge the functioning of single-copula model, we employed the log-likelihood value and the AIC & the Bayesian information criteria (BIC) for the goodness-of-fit test. The results in Table S3 revealed that out of the six unique copulas covered in the current analysis, the copula parameter (ρ) estimates are significant in all the paired stock markets in the case of Gaussian, student-t copula, Clayton (u, v), and Clayton ($1-u$, $1-v$). However, in the case of the rotated Clayton copula and rotated survival Clayton copula, the parameter estimates are insignificant for all the paired stock markets.

Among the six estimated functions, the rotated Clayton copula (half rotated) reveals the largest LL values in 7 out of 21 paired stock markets, and rotated survival Clayton copula (half rotated) exhibits the largest LL values in 14 out of 21 paired stock markets. The student-*t* copula delivers the lowest AIC and BIC values in 19 out of 21 paired stock markets, which is in sync with the findings of Wang et al. (2013). The student-*t* copula has an underlying assumption that pertains to symmetrical tail dependence, inferring uniformity between the stock markets, when the stock markets are together in booming phase and, likewise, in the bearish phase. However, this assumption may be limited in the empirical centric case. Therefore, to envelop the asymmetric tail dependence, the current study investigates the dependence framework between the paired stock markets through a dependence-switching copula model identical to that of Wang et al. (2013).

Table 1 reveals the outcomes of dependence-switching copula model for each of the paired stock market. Results demonstrate that the copula parameter estimates (α_1) and (α_2) under distinct regimes are significant for the paired stock markets. Moreover, in the dependence-switching copula, the estimated LL (AIC and BIC) is larger (smaller) in comparison with the single-copula models for all the paired stock markets. This substantiates the applicability of employing the dependence-switching copula model to inspect the dependence structure among the selected stock markets. P_{11} and P_{00} report high and significant values, thereby revealing that the duration of each regime is long and a switch between the regimes is not generally identified. A further benefit about this approach is that it permits analysis of dependence (ρ_i) and tail dependence (φ_i) between the paired stock markets in up to four different settings: (a) bear stock markets associated with bull stock markets; (b) bull stock markets associated with bear stock markets; (c) bear stock markets linked with bear stock markets; and (d) bull stock markets linked with bull stock markets. Billio and Pelizzon (2000) highlighted that the value at risk (VaR) for a portfolio manifests an estimation of a definite probability distribution percentile of the portfolio change in value over a set investment period. Detection of significant tail dependence manifests a higher likelihood of extreme events, which advocates a higher VaR estimation than that implied through bivariate normal distribution. Therefore, neglecting to study the significance of tail dependence shall lead to the miscalculation of risk. Thus, accurate tail dependence estimates are pertinent for calculating VaR and thereby for effective risk management.

A negative correlation regime encompasses of a period where a bull (bear) stock market synchronizes with a low (high) stock price in other markets. Left tail dependence (φ_3) signifies the probability of concurrently experiencing huge losses in stock markets and substantial profits in the other stock markets; the opposite is valid for right tail dependence (φ_4). Realizing high values for φ_3 (φ_4) shows that the prospect of a stockholder encountering enormous losses is very high if he or she maintains a long (short) position in the stock market and a short (long) position in the other stock market. Thus, an adequate understanding of tail dependence is of paramount importance for the portfolio management of a risk-reluctant investor (Susmel, 2001). Panel B of Table 1 clarifies the negative correlation regime. Results of Panel B reveal that the estimations of left dependence (ρ_3) are significant for 7 out of 21 paired stock markets, whereas the estimations of left tail dependence (φ_3) are significant for 6 out of 21 paired stock markets. Panel B results also show that the estimates of right dependence (ρ_4) are significant for only 2 of the 21 paired stock markets, whereas the estimates of right tail dependence (φ_4) are significant for 3 out of 21 paired stock markets. In the case where

Table 1. Estimation of the dependence-switching copula model.

	China–India	China–Indonesia	China– SK	China–Turkey	China–Brazil	China–Mexico	India–Indonesia	India–SK	India–Turkey	India–Brazil	India–Mexico
						Panel A: Positive correlation regime					
Both markets are bearish											
α_1	**0.4005**	**0.4943**	**0.6536**	**0.1858**	**0.1824**	**0.3549**	**0.7015**	**0.9393**	**0.4687**	**0.3919**	**0.4884**
	(0.0674)	(0.0898)	(0.0756)	(0.0464)	(0.0427)	(0.1208)	(0.0666)	(0.0614)	(0.0605)	(0.0618)	(0.0004)
ρ_1	**0.2590**	**0.3063**	**0.3773**	**0.1331**	**0.1309**	**0.2345**	**0.3967**	**0.4811**	**0.2938**	**0.2545**	**0.3034**
	(0.0355)	(0.0431)	(0.0312)	(0.0302)	(0.0280)	(0.0665)	(0.0263)	(0.0196)	(0.0298)	(0.0328)	(0.0002)
φ_1	**0.0886**	**0.1230**	**0.1731**	0.0120	0.0112	0.0709	0.1861	0.2390	0.1139	0.0853	0.1210
	(0.0258)	(0.0313)	(0.0212)	(0.0112)	(0.0010)	(0.0471)	(0.0175)	(0.0115)	(0.0218)	(0.0238)	(0.0001)
Both markets are bullish											
α_2	0.3449	0.4131	0.3777	0.1408	0.1330	0.4067	0.4613	**0.4575**	0.3191	0.2665	0.1863
	(0.0701)	(0.0902)	(0.0713)	(0.0453)	(0.0409)	(0.1309)	(0.0558)	**(0.0507)**	(0.0558)	(0.0591)	(0.0350
ρ_2	**0.2290**	**0.2657**	**0.2469**	**0.1031**	**0.0978**	**0.2623**	**0.2902**	**0.2883**	**0.2144**	**0.1836**	**0.1334**
	(0.0389)	(0.0469)	(0.0384)	(0.0309)	(0.0281)	(0.0685)	(0.0277)	**(0.0252)**	(0.0318)	(0.0355)	(0.0228)
φ_2	0.0670	0.0934	0.0798	0.0036	0.0027	0.0909	0.1113	**0.1099**	0.0569	0.0371	0.0121
	(0.0274)	(0.0342)	(0.0276)	(0.0058)	(0.0044)	(0.0499)	(0.0202)	**(0.0184)**	(0.0217)	(0.0214)	(0.0085)
						Panel B: Negative correlation regime					
Bear stock markets associated with bull stock markets											
α_3	−0.0571	0.0029	−0.0351	0.9146	0.0599	0.0653	−0.0696	−0.082	−0.1669	−0.1503	0.2490
	(0.0468)	(0.0450)	(0.0466)	(0.5234)	(0.1407)	(0.0677)	(0.0966)	(0.1681)	(0.0674)	(5.19E-1)	(0.001)
ρ_3	−0.0462	0.002	−0.0280	**0.4732**	0.0457	0.0496	−0.0566	−0.0671	−0.1425	**-0.1274**	**0.1731**
	(0.0389)	(0.0353)	(0.0379)	(0.1705)	(0.1041)	(0.0498)	(0.0813)	(0.1433)	(0.0624)	(4.73E-1)	**(0.0007)**
φ_3	92939.6	5.48E-105	1.89E + 08	0.2343	4.80E-06	1.23E-05	1.05E + 04	2344.477	3.18E + 01	**50.2206**	**0.0309**
	(923388.7)	(2.04E-101)	(4.96E + 09)	(0.1016)	(0.0001)	(0.0001)	(145266.7)	(40633.85)	(5.33E + 01)	(7.99E-06)	(0.0004)
Bull stock markets associated with bear stock markets											
α_4	−0.0551	**-0.1241**	−0.0834	1.9365	−0.0199	−0.0494	−0.1212	−0.1246	0.1301	−0.0542	−0.1887
	(0.0528)	(0.0341)	(0.0448)	(1.5732)	(0.1238)	(0.0699)	(0.0746)	(0.0826)	(0.1502)	(0.0717)	(0.1382)
ρ_4	−0.0445	**-0.1037**	−0.0683	**0.6981**	−0.0159	−0.0398	−0.1011	−0.1042	0.0958	−0.0437	−0.1629
	(0.0438)	(0.0303)	(0.0383)	(0.2284)	(0.0992)	(0.0576)	(0.0661)	(0.0734)	(0.1035)	(0.0594)	(0.1305)
φ_4	144027.4	133.4078	2036.352	**0.3496**	**5.81E + 14**	618353.6	152.552	130.3868	0.0024	179116.2	19.6816
	1733416	204.764	9094.144	0.1016	1.2411	12263146	537.5603	481.2953	0.0149	3028893	52.9243
						Panel C: Regime Switching					
P_{11}	**0.9992**	**0.9993**	**0.9995**	**0.9771**	**1**	**0.9571**	**1**	**0.9990**	**0.9986**	**0.9985**	**0.9989**
P_{00}	**0.9987**	**0.9992**	**0.9989**	**0.5527**	**0.9989**	**0.9728**	**0.9984**	**0.9937**	**0.9945**	**0.9954**	**0.9939**
LL	10549.3	10534.7	10465.9	10602.9	10598.6	10589.9	10325.1	10292.4	10447.6	10523.3	10503.8
AIC	−21138.5	−21109.3	−20971.79	−21245.71	−21237.1	−21219.76	−20690.2	−20624.7	−20935.2	−21086.5	−21047.5
BIC	−21268.5	−21239.25	−21101.71	−21375.63	−21367.03	−21349.68	−20820.1	−20754.6	−21065.1	−21216.5	−21177.4

(*Continued*)

Table 1. Continued

	Indonesia–SK	Indonesia–Turkey	Indonesia–Brazil	Indonesia–Mexico	SK–Turkey	SK–Brazil	SK–Mexico	Turkey–Brazil	Turkey–Mexico	Brazil–Mexico
Panel A: Positive correlation regime										
Both markets are bearish										
α_1	**0.9152**	**0.3555**	**0.3336**	**0.3025**	**0.5177**	**0.2865**	**0.3843**	**0.6724**	**0.5460**	**1.4082**
	(0.0800)	(0.0537)	(0.0573)	(0.0460)	(0.1255)	(0.0438)	(0.0469)	(0.0801)	(0.0768)	(0.0726)
ρ_1	**0.4733**	**0.2348**	**0.2226**	**0.2049**	**0.3174**	**0.1956**	**0.2505**	**0.3849**	**0.3305**	**0.6044**
	(0.02608)	(0.0295)	(0.0322)	(0.0267)	(0.0590)	(0.0258)	(0.0251)	(0.0325)	(0.0352)	(0.0156)
φ_1	**0.2345**	**0.0711**	**0.0626**	**0.0505**	**0.1310**	**0.0444**	**0.0823**	**0.1783**	**0.1405**	**0.3056**
	(0.01554)	(0.0209)	(0.0223)	(0.0176)	(0.0425)	(0.0165)	(0.0181)	(0.0219)	(0.0251)	(0.0077)
Both markets are bullish										
α_2	**0.7643**	**0.3835**	**0.2382**	**0.1886**	**0.2385**	**0.2271**	**0.1842**	**0.2679**	**0.4673**	**0.9231**
	(0.0804)	(0.0562)	(0.0634)	(0.0457)	(0.0600)	(0.0422)	(0.0421)	(0.0492)	(0.1402)	(0.0586)
ρ_2	**0.4207**	**0.2500**	**0.1664**	**0.1349**	**0.1666**	**0.1595**	**0.1321**	**0.1845**	**0.2931**	**0.4760**
	(0.0299)	(0.0301)	(0.0392)	(0.0297)	(0.0370)	(0.0264)	(0.0275)	(0.0295)	(0.0691)	(0.0189)
φ_2	**0.2018**	**0.0820**	0.0272	0.0126	0.0273	0.0236	0.0116	0.0376	0.1134	0.2359
	(0.0192)	(0.0217)	(0.0211)	(0.0112)	(0.0199)	(0.0134)	(0.0100)	(0.0178)	(0.0504)	(0.0112)
Panel B: Negative correlation regime										
Bear stock markets associated with bull stock markets										
α_3	**-0.1473**	0.0369	−0.0009	0.0579	−0.1487	**0.1198**	−0.1329	**-0.1463**	−0.0773	**-0.1573**
	(1.57E-07)	(0.1076)	(0.0625)	(0.3146)	(0.0680)	(9.82E-08)	(0.2240)	(3.75E-07)	(0.0683)	(3.69E-07)
ρ_3	**-0.1245**	0.0285	−0.0007	0.0441	−0.1258	**0.0886**	−0.11166	**-0.1236**	−0.0631	**-0.1337**
	(1.42E-07)	(0.0814)	(0.0491)	(0.2331)	(0.0618)	(6.84E-08)	(0.2006)	(3.40E-07)	(0.0579)	(3.39E-07)
φ_3	**55.2616**	3.55E-09	Inf	3.11E-06	52.8733	**0.0015**	91.73623	**57.02809**	3907.793	**40.9619**
	(0.0003)	(1.94E-07)	(0.7529)	(0.0002)	(112.575)	(7.29E-09)	(805.4187)	(0.0007)	(30933.6)	(0.0004)
Bull stock markets associated with bear stock markets										
α_4	−0.0837	−0.1118	−0.0536	−0.0024	−0.11542	−0.1659	−0.0871	−0.0941	−0.1616	−0.1702
	(0.0796)	(0.0904)	(0.0541)	(0.1375)	(0.0867)	(0.12407)	(0.37405)	(0.0896)	(0.0893)	(0.0902)
ρ_4	−0.0685	−0.0928	−0.0432	−0.0017	−0.0961	−0.1416	−0.0715	−0.0775	−0.1376	−0.1456
	(0.0679)	(0.0793)	(0.0448)	(0.1083)	(0.0764)	(0.1147)	(0.3203)	(0.0773)	(0.0822)	(0.0838)
φ_4	1970.107	247.0389	206672.1	**1.42E + 127**	202.8455	32.6128	1420.632	789.661	36.4304	29.3082
	(15519.5)	(1239.643)	(26994)	(1.6329)	(915.0826)	(101.8942)	(48477.84)	(5535.288)	(86.3387)	(63.2526)
Panel C: Regime Switching										
P_{11}	**0.9902**	**1**	**0.9981**	**1**	**0.9990**	**0.9993**	**0.9991**	**0.9988**	**0.9987**	**0.9992**
P_{00}	**0.9693**	**0.9988**	**0.9964**	**0.9960**	**0.9937**	**0.9930**	**0.9941**	**0.9939**	**0.9941**	**0.9935**
LL	10209.8	10492.3	10562.2	10548.01	10479.4	10539.2	10512.3	10428.3	10434.7	9749.26
AIC	−20459.5	−21024.5	−21164.41	−21136.02	−20998.73	−21118.4	−21064.6	−20896.5	−20909.3	−19538.5
BIC	−20589.4	−21154.5	−21294.34	−21265.943	−21128.65	−21248.32	−21194.5	−21026.51	−21039.2	−19668.4

Note: α_i is the shape parameter of the dependence-switching copula, and ρ_i and φ_i are the measures of dependence and tail dependence, respectively. The numbers in parentheses are standard deviations. Bold-faced values represent significance at the 5% level. LL, AIC, and BIC denote the estimated log-likelihood value based on equation (4), the Akaike information criterion, and the Bayesian information criterion, respectively. P_{11} and P_{00} are two transition probabilities. Values are in the order of first parameter and the standard error. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.
Source: Author's Estimation.

bear stock markets are synced with bull stock markets, the estimates of the left dependence (ρ_3) ranges from .1309 to .6044 and those of tail dependence (φ_3) ranges from .0111 to .3056. Conversely, when bull stock markets are linked with bear stock markets, the estimates of the right dependence (ρ_4) and tail dependence (φ_4) ranges from .03026 to .3203 and from .0027 to .2359, respectively.

The pair of South Korea–Brazil (India–Turkey) has the lowest tail dependence when a bear (bull) stock market is linked with the bull (bear) stock market. A stockholder possessing a long (short) position in one stock market and a short (long) position in the other stock market witnesses the least systemic risk for the mentioned markets. For the positive correlation regime, there are two scenarios. First, a bear stock market coexists with a low stock price in other market (paired markets are busting). Second, a bull stock market is commented with a high stock price of other stock market (paired markets are advancing). Left tail dependence (φ_1) exhibits the probability of substantial loss (both the stock markets are busting), and the right tail dependence (φ_2) shows the probability of huge gains (both markets are booming). If (φ_1) or (φ_2) is high, then a long (short) position in both markets will experience massive losses (profits).

In the positive correlation regime of Panel, A in Table 1, the estimates of the left dependence (p_1) range from .1309 in China – Brazil pair to .6044 in Brazil – Mexico pair, and the left tail dependence (φ_1) vary from .0111 to .3056. The estimates of right dependence (p_2) range from -10325.1 to 0.4759, and those of right tail dependence (φ_2) range from 0.0027 to 20820.14. The estimates of left dependence (p_1) are significant for all the 21 paired stock markets, and the estimates of left tail dependence (φ_1) are significant for the eighteen paired stock market. In contrast to the left dependence, the estimates of right dependence (p_2) are significant for all the 21 paired stock markets and those of right tail dependence (φ_2) are significant for only 8 paired stock markets. The results demonstrate that estimates of tail dependence are mostly higher when both the stock market indices are busting compared with when both the markets are advancing. This signify that the prospect of experiencing huge losses (gains) concurrently in both markets is mostly excessive (low) for a stockholder with long positions when both the markets are considered.

Through the four extreme returns scenarios, the paired stock indices of South Korea–Brazil have the lowest tail dependence when both the stock markets are bearish, and the paired stock indices of China–Brazil have the lowest tail dependence when both the markets are bullish. This result substantiates that China–Brazil (South Korea–Brazil) has the lowest systemic risk when both the markets are bullish (bearish); therefore, a stockholder taking short or long position in both the markets bears the minimum systemic risk. Similarly, the paired stock indices of South Korea–Brazil has lowest tail dependence in the case of bear stock markets being linked with bull stock markets, and China–Turkey has the lowest tail dependence, in the case of bull stock markets being linked with bear stock markets. A stockholder taking a long (short) position in the third case, but a short (long) position in the fourth case, undergoes the minimum systemic risk for South Korea–Brazil (China–Turkey). In sum, the tail dependences exhibited in Table 1 are the actual systemic risks ensuing from the different extreme return scenarios. These are vital for the risk-averse investors and for proper estimation of VaR.

By linking the survival Clayton and the Clayton copulas, Ning (2010) proposed the empirical evidence for the symmetric tail dependence when both the stock markets and

Table 2. Wald test for symmetric dependence and symmetric tail dependence.

	Symmetric dependence under a negative correlation regime (one booming market associates with the other crashing market)																					
	China–India		China–Indonesia		China–SK		China–Turkey		China–Brazil		China–Mexico		India–Indonesia		India–SK		India–Turkey		India–Brazil		India–Mexico	
Wald test	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value
$\rho3 = \rho4$	0.2405	0.6238	0.2885	0.5912	4.764	0.0291	0.3886	0.533	0.5084	0.4758	0.1183	0.7309	5.1113	0.0238	18.9258	0	2.5481	0.1104	1.9415	0.1635	16.3175	0.0001
$\varphi3 = \varphi4$	0.0006	0.98	4.1754	0.041	0.411	0.5215	0.6504	0.42	0.1091	0.7412	1.5401	0.2146	0.1314	0.717	0.0767	0.7818	3.8238	0.0505	1.1882	0.2757	3.1744	0.0748
	Symmetric dependence under a positive correlation regime (both markets are booming and crashing)																					
Wald test	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value
$\rho1 = \rho2$	0.2425	0.6224	0.2902	0.5901	4.9437	0.0262	0.3691	0.5435	0.4742	0.4911	0.1187	0.7304	5.1793	0.0229	18.9546	0	2.6532	0.1033	2.0492	0.1523	32.5206	0
$\varphi1 = \varphi2$	0.0006	0.9813	0.4245	0.5147	0.0015	0.9696	0.6725	0.4122	0	0.9963	0.0025	0.9598	0.0051	0.9432	0.003	0.9564	0.3556	0.551	0.0035	0.9529	0.1376	0.7107

(*Continued*)

	Symmetric dependence under a negative correlation regime (one booming market associates with the other in crashing)																			
	Indonesia–SK		Indonesia–Turkey		Indonesia–Brazil		Indonesia–Mexico		South Korea–Turkey		South Korea–Brazil		South Korea–Mexico		Turkey–Brazil		Turkey–Mexico		Brazil–Mexico	
	Test	p-value	Test	p-value	Test	P-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value
$\rho3 = \rho4$	1.2534	0.2629	0.0842	0.7717	1.0163	1.0163	2.0615	0.1511	7.5277	0.0061	0.6093	0.435	6.8337	0.0089	16.1075	0.0001	0.2495	0.6174	15.9409	0.0001
$\varphi3 = \varphi4$	3.1341	0.0767	0.7204	0.396	0.3267	0.3267	0.0301	0.8623	0.0782	0.7798	3.2324	0.0722	0.0053	0.942	4.0416	0.0444	0.5895	0.4426	−0.0203	1
	Symmetric dependence under a positive correlation regime (both markets are booming and crashing)																			
	Test	p-value	Test	p-value	Test	P-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value	Test	p-value
$\rho1 = \rho2$	1.2429	0.2649	0.0843	0.7716	NaN	NaN	2.2661	0.1322	7.1857	0.0073	0.6216	0.4305	8.2942	0.004	19.2285	0	0.2469	0.6193	15.4735	0.0001
$\varphi1 = \varphi2$	0.0152	0.902	0.0397	0.842	NaN	NaN	0	1	0.0253	0.8735	0.1024	0.749	0.0007	0.9786	0.017	0.8963	0.0157	0.9004	−0.0092	1

Source: Author's Estimation.

the foreign exchange markets are busting or advancing. Accordingly, this present study assesses whether the hypotheses pertaining to symmetric dependence and tail dependence are substantiated by testing the validity of $\rho 3 = \rho 4$ and $\varphi 3 = \varphi 4$, correspondingly, in the scenario of a negative correlation regime when one booming stock market associates with a crashing stock market. We employed a Wald test to inspect the symmetric dependence and symmetric tail dependence among the paired stock markets. The first panel of Table 2 shows that the hypotheses of $\rho 3 = \rho 4$ are rejected for 8 out of 21 paired stock markets, namely, China–South Korea, India–Indonesia, India–South Korea, India–Mexico, South Korea–Turkey, South Korea–Mexico, Turkey–Brazil, and Brazil–Mexico at the conventional levels. Meanwhile, the hypotheses of $\varphi 3 = \varphi 4$ are rejected for 6 out of 21 paired stock markets, namely, China–Indonesia, India–Turkey, India–Mexico, Indonesia–South Korea, South Korea–Brazil, and Turkey–Brazil at the conventional level. The rejection of the hypotheses for eight and six paired stock markets revealing asymmetry owing to the financial crisis or economic reforms in the respective

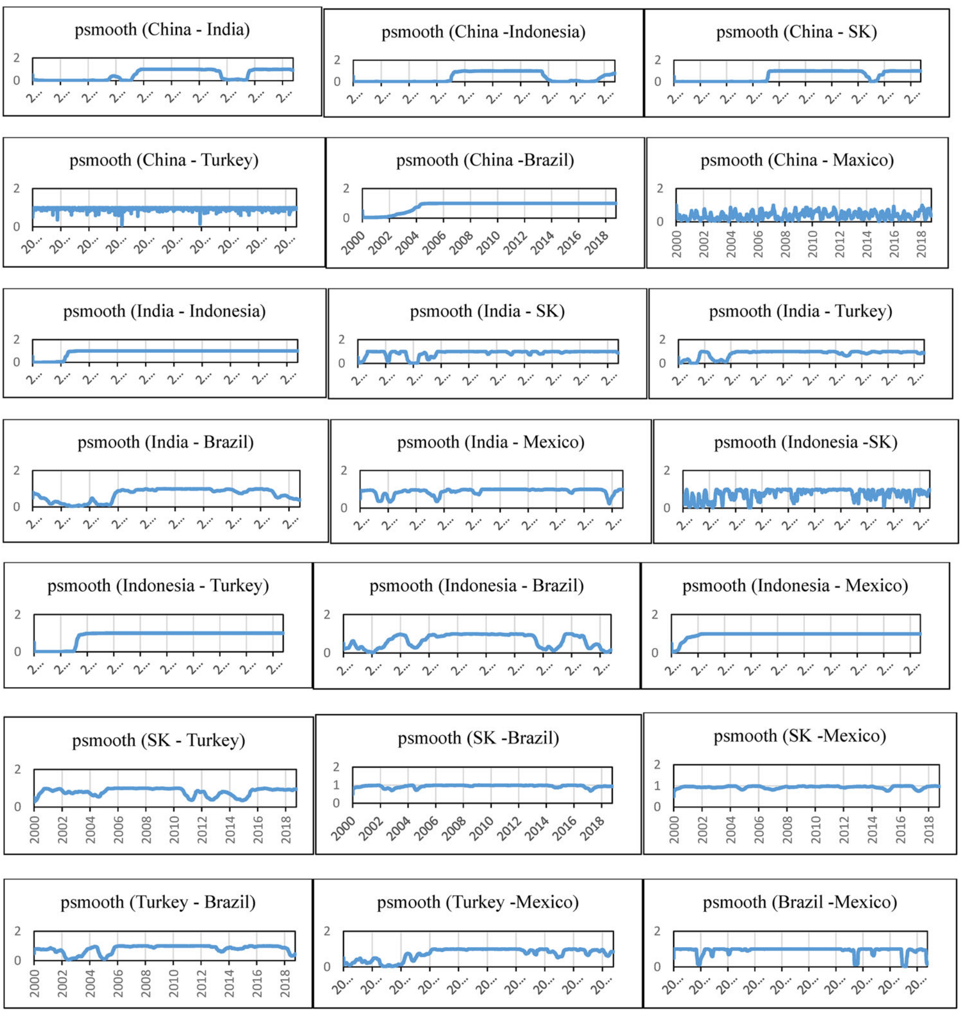

Figure 1. Smoothing probability of the positive correlation regime between the paired stock markets.
Source: Calculated by the authors.

economies. Thus, under the negative correlation regime, symmetric dependence and symmetric tail dependence occurred in most of the paired stock markets.

Likewise, the current study explores the hypotheses of symmetric dependence and tail dependence in the scenario of a positive correlation regime by assessing the validity of ρ1 = ρ2 and φ1 = φ2, (both markets are booming and crashing). From the Table 2, it is revealed that the hypotheses of ρ1 = ρ2 are rejected for 8 out of 21 paired stock markets, namely, China–South Korea, India–Indonesia, India–South Korea, India–Mexico, South Korea–Turkey, South Korea–Mexico, Turkey–Brazil, and Brazil–Mexico. The hypotheses of φ1 = φ2 are not rejected for all the covered emerging stock markets at the conventional levels. Accordingly, symmetric dependence occurs in the majority

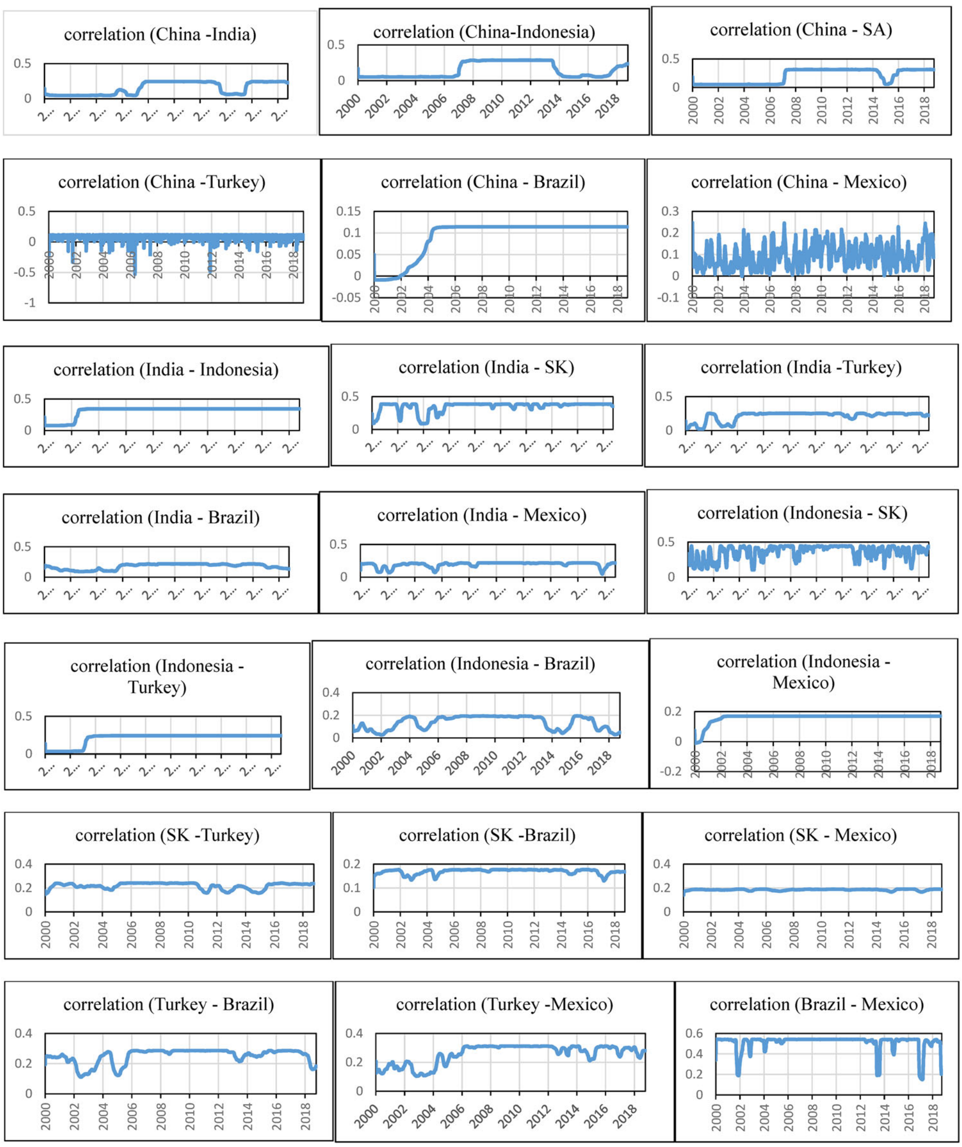

Figure 2. Smoothing correlation coefficients between the paired stock markets.
Source: Calculated by the authors.

of paired stock markets, whereas symmetric tail dependence is present in totality for all the covered markets. The likely rationale for the outcome of symmetrical dependence and tail dependence may be owning to fast expansion and better macroeconomic conditions and capital market process.

Figure 1 reveals the smoothing probability of the positive correlation regime between the paired stock markets. From the figure, we can deduce that portfolio rebalancing dominates in 14 out of 21 cases of stock market. In terms of volatility, Chinese stock market has evidently more cases of low range of volatility with other selected stock markets. Likewise, the Indonesian stock market reveals the low range of volatility with the other stock markets. Moreover, Brazilian stock market reveals more cases of medium range of volatility with other stock markets. Likewise, the Indian stock market demonstrates more cases of medium range of volatility with other stock markets. Similar traits are revealed in the stock markets of Turkey, Mexico, and South Korea. Figure 2 presents the smoothing correlation coefficients between the paired stock markets.

5. Conclusion and policy implications

The present study employs copula to examine the dependence and tail dependence structure of the emerging stock markets. Precise tail dependence estimations are necessary for effective risk management. Failing to investigate the significance of tail dependence will result in risk underestimation. This study unearths the dependence structure among the seven emerging stock markets through a dependence-switching copula model by Wang et al. (2013). The unique attribute of this approach is that it allows investigation of dependence (ρ_i) and tail dependence (φ_i) between the paired stock markets in up to four different settings: (a) bear stock markets associated with bull stock markets; (b) bull stock markets associated with bear stock markets; (c) bear stock markets associated with bear stock markets; and (d) bull stock markets associated with bull stock markets.

Estimating the model with daily stock market indices for seven stock markets from 2000 to 2018, this study has uncovered noteworthy insights. The results of the study reveal varying nature of dependence structure of emerging stock markets. Under the negative correlation regime, only 8 out of 21 paired stock markets, namely, China - South Korea, India - Indonesia, India - South Korea, India - Mexico, South Korea -Turkey, South Korea - Mexico, Turkey - Brazil, and Brazil - Mexico, have asymmetric dependence, and 6 out of 21 paired stock markets, namely, China - Indonesia, India - Turkey, India -Mexico, Indonesia - South Korea, South Korea - Brazil, and Turkey -Brazil, have asymmetric tail dependence during the stipulated time period. Thus, dependence and tail dependence for most of the paired stock market are symmetric in nature during the stipulated period under the negative correlation regime. By contrast, in the positive correlation regime, 8 out of 21 paired stock markets, namely, China -South Korea, India - Indonesia, India - South Korea, India -Mexico, South Korea - Turkey, South Korea - Mexico, Turkey - Brazil, and Brazil -Mexico, are asymmetric in dependence, and all the paired stock markets are symmetrical in stipulated regime. Accordingly, dependence and tail dependence for most of the paired stock markets are symmetric in nature under the positive regime.

Our findings revealed pertinent implications from the perspective of asset pricing and risk management. Although the emerging stock markets are deemed by the global investors to be a homogenous class, these stock markets manifest varied degree of traits. Henceforth, from a portfolio diversification perspective, the global investors can exploit the diversification opportunities offered by the selected stock markets. As a result, asset allocation that considers this varying dependence structure may contribute to portfolio returns that are optimal.

In terms of risk prediction and portfolio management, our findings have significant implications for financial investors and risk managers. Our results of upside and downside risk, in particular, can facilitate the creation of asymmetrical investment strategies. Policymakers, market participants, and international investors will be interested in these findings. Policymakers should develop a roadmap to decipher the effects of any risk on the selected emerging stock markets. Market players and international investors should account for the extreme market conditions in their models when making portfolio management decisions. Further, the authorities should examine the amount of financial cooperation they want to pursue, spanning from harmonization of laws and regulations, covering collaboration to offering of convenient access to the selected emerging markets. Furthermore, we urge that future work use a dependence-switching copula model on various time scales to comprehend the dependence between these emerging stock markets.

Notes

1. We have E7 economies in the current study, while Russia is part of E7 economies but on account of convergence issues in Russian data, we have excluded it. Further we have included South Korea on account of substantial weight in the MSCI Emerging Markets Index.
2. Kumar et al. (2019) covered on BRICS foreign exchange and exchange market, while this paper is on Stock Market dependence of (E7) Emerging seven economies.
3. Wang et al. (2018) proposed that the Gumbel copula could be a reliable substitute even though fails to sync rightly in accordance to model selection criteria like the Akaike information criteria.

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