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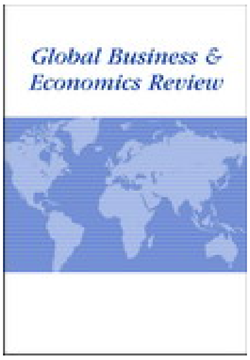

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Modelling long memory dependence structure using FIGARCH-copula approach – evidence from major Asian stock markets

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Abstract: Increased volatility in the stock markets has led the market to originate a new variety of techniques to predict markets efficiently. The aim of the study is to scrutinise the potential dependence among different Asian stock markets, using the FIGARCH copula approach. In the first step, the marginal distribution for the copula has been estimated with the best-fit approach using minimum AIC on the underlying assumptions of normal, Student-t and generalised error distribution (GED). The results indicate that Student-t best fits for the return series SHANGHAI and NIKKEI, while GED for the HANG SENG, KOSPI and NIFTY. In the next step, we have used Gaussian, Student-t, and Clayton copula to estimate the parameters and the dependence measures. The performance of the three copula distributions has been compared based on AIC and BIC criteria. We find t-copula performs better than the other two copula functions.

Keywords: long memory; volatility forecasting; stock market; fractionally integrated-GARCH; copula.

JEL codes: G10, G170, G1, C190, F30.

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1 Introduction

Persistence or long-run memory in financial time series is an area of continuing interest to researchers, analysts and investors. Empirical studies exploring the absorption of information in the markets post volatility shocks due to extreme events have shown that markets react gradually over a period of time (Bhatia and Gupta, 2020; Spelta et al., 2021; Wang et al., 2021). The long-run effects of volatility realised in longer periods refute the notion of market efficiency proposed by Fama and French (1992), thus creating significant implications for the traders, analysts and risk managers. Markets in both developed and developing countries experience a detrimental impact of unprecedented volatility in asset markets driven by extreme events like the Asian financial crisis, global financial crisis (GFC), trade wars, etc., and more recently, pandemic like COVID.

Asian stock market is considered to be the most integrated with the cross-border financial system and have increased the investment flows significantly especially after the GFC in 1997 (Caporale et al., 2019). A country's economy is typically seen to gain from cross-border financial integration since it lowers the cost of trading assets and provides more options for portfolio diversification. To eliminate the inefficiencies brought on by the prior limits on capital movements and improve welfare, numerous Asian nations launched regional financial deregulation initiatives (Haini, 2020). As compared to G-7, Asian stock markets earned better stock with time but have tended to be more volatile. Asia's markets underperformed the G-7 during the AFC in terms of the average risk-return trade-off. Excluding the GFC, they recorded their highest volatility and lowest returns during this period. At the time of GFC, all regions reported their worst performance. Except for India, Malaysia, the Philippines, and Thailand, stock markets recorded negative returns and faced higher volatility. Although stock returns have tended to be greater than those of G-7 counterparts they also faced higher volatility in their markets (Lipinsky and Ong, 2014). It can be argued that the stock markets are interconnected, requiring investors need to make the appropriate financial decisions, especially to indicate the weight of each stock market in order to maximise returns and to minimise their risk.

There are some studies that indicate that the degree of market development enhances the return-generating processes and helps to find out long memory dependence (Bouri et al., 2019; Mensi et al., 2019). On the same note, Boako et al. (2019) have investigated the moves of the Indian stock market on other markets in Asia and the USA in the period of capital market reforms by examining the tools of cointegration, vector autoregression, vector error-correction models and Granger causality models. However, these approaches are used commonly to model risks, but fail to analyse the nonlinear dependence.

Additionally, a nonlinear dependence pattern in the data cannot be captured by the linear correlation coefficient. Copulas offer a solution to the shortcomings of the linear correlation coefficient. Since the development of copula theory by Sklar (1959), its use in financial modelling has found more attention of the academicians and practitioners recently (Luo et al., 2021; Dewick and Liu, 2022).

Financial time series frequently display the volatility clustering and is a phenomena well documented in the financial literature. Since the introduction of volatility clustering phenomena (Engle, 1982; Bollerslev, 1986), there have been manifold variations in the ARCH volatility models that have been developed. The application of ARCH models in various asset markets globally for risk optimisation has provided a good surrogate for modelling risk in just like real situations. Given the nature of financial time series that are commonly heteroskedastic, the ARCH models have been extensively applied to financial data at various frequencies, making them ideal for modelling. However, to calculate market risk more precisely, we have considered both the assets' volatility and the interdependence between them using copula-GARCH.

Various extensions of generalised autoregressive conditional heteroskedasticity (GARCH) models have been developed over time to capture the *leverage effects* observable in financial time series. As an improvement over traditional GARCH that captures short memory, IGARCH offers flexibility in terms of absenting the unconditional variance and making the persistence of conditional variance infinite. The IGARCH model is viewed as too restrictive criticised for applications in times series that are mean-reverting (Tayefi and Ramanathan, 2016). A better modification of IGARCH is fractionally integrated generalised autoregressive conditional heteroscedasticity (FIGARCH) that introduces a fractional differencing parameter that offers flexibility to represent the temporal dependencies of financial time series (Baillie et al., 1996).

In line of the above discussion, the study aims to analyse the presence of long-term dependence and multifractal parameters in the stock indices, especially in the Asian stocks' indexes in order to forecast the volatility. The study also aims to examine the symmetry in the variation trends of the nonlinear structure of financial time series, which aid in performing better portfolio management and risk management. The study investigates the correlations between returns of five indices (HANGSENG, SHANGHAI, KOSPI, NIKKEI and NIFTY) by using copula-FIGARCH model to analyse the parameter estimates, dependence measures, and the fit statistics for the Gaussian, Student-t, and Clayton copula in order to fill the gap in the literature on modelling dependence structures. The study adds new knowledge to the existing literature in understanding the nonlinear dependence of the financial markets, particularly the stock markets in Asian context and expected to aid the policy formulation for regulators and decision making for portfolio optimisation by international investors during the time of crisis.

2 Previous studies

Measurement and forecasting of volatility have been an area of continued interest to analysts and researchers for obvious applications in the field of asset allocation, pricing, and framing of risk management strategies. With the introduction of GARCH models, the conditional volatility in developed markets is extensively examined by researchers. Studies like Arouri et al. (2012), Niu and Wang (2013), Chkili et al. (2014), Ibragimov and Lentzas (2017) and Mokni and Mansouri (2017) have examined the presence of long memory in developed markets and find contrasting evidence of persistence.

While a significant number of studies in the USA and other developed markets refute the tail dependence and asymmetric structures, the studies on European markets have shown contrasting results. Results of the analysis of long-run memory in Greek stock markets studies obtained by Barkoulas et al. (2000) are contrary to the phenomenon of developed stock markets. Kumar and Maheswaran (2013) study of Portugal, Italy, Greece, Ireland, and Spain shows asymmetry and long-range dependence in the conditional volatility of the stock returns. Romanian stock market for the pre-crisis and post-crisis periods evidences high persistence in volatility, long memory and leverage effect with nonlinearities (Pece and Petria, 2015). Costa (2017) study on US markets for the period 1986–2016 shows that forecast results of IGARCH are different from conventional GARCH estimations. The study conducted by Emenogu et al. (2020) on Nigerian stock market to examine conditional volatility and VaR measures during the period show persistence. An empirical examination by Ahmed and Suliman (2011) for the Khartoum Stock Exchange (KSE) during the period from January 2006 to November 2010 show that the conditional variance process is highly persistent (explosive process), and provide evidence on the existence of risk premium for the KSE index return series which support the positive correlation hypothesis between volatility and the expected stock returns.

Li et al. (2008) find FIGARCH as the best fit to indicate the conditional heteroscedasticity in time series with high volatility. Studies also described the role of multivariate normal distribution over the linear correlation to describe the dependence measure. However, a simple exploratory and graphical analysis of both returns and volumes distributions suggest that fat tails, long memory, heteroscedasticity, clustering, and other non-Gaussian features are important measures to examine the tail dependence phenomenon. Antonakakis (2012) examination of volatility of exchange rates for industrialised and developing countries show that among all heteroscedastic models, FIGARCH fitted the data better.

The assumption of unconditional variance being constant has shown the presence of long-run memory in the works of McMillan and Thupayagale (2011). However, the study of Kang et al. (2009) on sudden changes in volatility for Japanese and Korean stock markets at points of volatility in 1986 shows the disappearance of long-run memory. Similar results have also been obtained by Wang and Moore (2009) on some markets of the European Union.

Several studies have examined the dependence of volume, trading, volatility of Asian stock markets. Ning and Wirjanto (2009) have established an upper tail dependence between volume and stock returns of East Asian stock markets. Maheshchandra (2012) have investigated the volatility process for the Indian stock market during the Asian financial crisis and used GARCH measures and establish that range of long memory of in BSE index than the NSE. Naeem et al. (2014) find weak upper tail dependence between return and volume for Hong Kong and Indian stock indices. The leverage effect has been seen for Malaysia and Indonesia stock indices due to high volumes. Gil-Alana and Tripathy (2016) explored the long-range dependence techniques using fractionally integrated models to incorporate structural breaks and nonlinear structures. Duppati et al. (2017) have studied the presence of long range memory in major Asian markets using high-frequency data giving evidence of persistence. Sehgal et al. (2018) studied the dynamic integration in the south Asian equity markets. The study used copula GARCH models to analyse the inter-temporal integration of the stock market during 2004–2015. The findings show that very low levels of integration between the South Asian countries due to higher trade tariffs and less sophisticated equity markets with relatively weaker institutional and regulatory architecture. However, the extension of the study is imminently important to consider the period of crisis due to COVID-19. The present study can contribute more on the equity market integration especially with development of huge infrastructure and regulatory framework in the Asian region.

Li et al. (2020) used copula ARIMA-GARCH model to fit the marginal distributions and show that best fit with ARIMA(2, 1, 2) and GARCH(1, 1). The study show high degree of dependence in the emerging economies in comparison to developed countries. Jiang et al. (2021) used copula GARCH model toe examine the risk spillovers in the multiple markets. The study shows more accuracy in covariance measures and also able to analyse risk spillovers among the multiple stock markets instead of a single market. The US and Asian stock markets have suffered as a result of the COVID-19 pandemic shock. During the pandemic period, there is excessive risk spillovers from the USA to China, Japan, Hong Kong, and South Korea stock returns. The underlying connection has been studied by Zehri (2021). The findings demonstrate a significant stock market spillover from the US to East Asian markets. These spillovers intensify in the COVID-19 phase in comparison to the calm time. The recent studies however fails to capture the leverage effects present in the financial time series and also limited to study short memory using GARCH models.

Based on the literature, we find a strong motivation to attempt a study that can throw light on tail long dependence in major Asian stock markets. While a large number of studies have been attempted on analysing conditional volatility using GARCH, we supplement our methodology by integrating copula approach with FIGARCH. Our study covers a period that has evidenced shocks or extreme events creating a huge impact on the selected Asian markets.

3 Material and methods

This section explains the data and the statistical techniques and tools used in unveiling the dependency structure in the Asian stock markets. The Asian stock market is seen to be the most linked with the international financial system, and it has seen a major rise in investment flows, particularly after the 1997 GFC (Caporale et al., 2019). We have used the daily stock index values of all major Asia stock markets viz. HANG SENG of Hong Kong, SHANGHAI of China, KOSPI of Korea, NIKKEI of JAPAN and NIFTY of India from April 2016 to March 2021. It is observed that the economic posture of the selected nations in the sample indices reflect a high growth pattern with aggressive policy reforms and simultaneously faced shocks during the study period, as also argued by Duppati et al. (2017).

We have used copula-FIGARCH model to identify the structure of dependency in the time series. The FIGARCH, in comparison to IGARCH and other families of GARCH models (Bollerslev, 1986), offers more flexibility to represent the temporal dependencies of financial time series (Baillie et al., 1996). The analysis has been carried out using libraries (urca, ggplot2, tiger, fGarch, rugarch, dplyr) in R-environment. In order to estimate the parameters of FIGARCH, we have selected the best fit on the basis of

Akaike information criterion (AIC) and Bayesian information criterion (BIC) for the underlying assumption of normal, Student-t and generalised error distribution (GED). In the next phase, the marginal distributions are determined based on the residuals of the selected model of each time series.

3.1 Copula concept and measures of dependence

A copula measure of a dependence structure is a multivariate distribution function with the uniform marginal distribution of the time series. The dependence structure of copula measures the tail dependence of variables, i.e., the probability of variables in their upper (lower) quantile of the distribution. The tail dependence left (lower) and right (upper) denoted by α_t and $\alpha_r \in [0, 1]$ between X and Y can be defined following Sklar's (1959) theorem:

$$\alpha_t = \lim_{v \to 0} \Pr\left[G_Y(y) \le v \mid G_X(x) \le v\right] = \lim_{v \to 0} \frac{C(v, v)}{v}$$

$$\alpha_r = \lim_{v \to 1} \Pr\left[G_Y(y) \ge v \mid G_X(x) \ge v\right] = \lim_{v \to 1} \frac{1 - 2u + C(v, v)}{1 - v}$$

The different distributions in the family of copulas represent different dependence structures, with the association parameters indicating the strength of the dependence. For example, Clayton copula has a left tail while Gaussian has zero tail dependence. Copula models represent the function of the marginal distributions and thus correct specifications. We have used the FIGARCH, a special case of the GARCH model, to represent the marginal distributions of the copula models.

3.2 FIGARCH model

In order to study the dependence between the time series, the models for marginal distributions of each series in the pair need to be specified. The GARCH is a common approach to model time series with conditional heteroskedastic errors, professed by Bollerslev (1986) respectively. But these tools do not accommodate for long memory in volatility. In order to identify the long memory pattern, Baillie et al. (2007) professed the FIGARCH hereafter, which is a special case of the GARCH model, which allows for persistence of the conditional variance.

For any time series to model as FIGARCH(p, d, q), assume that $\{z_t\}$ the sequence of independent standard variate and $\{h_t = E(\varepsilon_t^2 \mid \varsigma_{t-1})\}$ is a positive time-dependent conditional variance, where $\varepsilon_t = z_t \sqrt{h_t}$ and $\varsigma_{t-1} \sim N(0, h_t)$. The model can be expressed following Baillie et al. (1996) as follows:

$$h_t = \omega_0 + \beta(L)h_t + \left[1 - \beta(L) - [1 - \phi(L)](1 - L)^d\right]\varepsilon_t^2$$

where L is the lag operator and $0 < d < 1$ is the long memory parameter. $\beta(L) = \beta_1 L + \cdots + \beta_1 L^p$, $\phi(L) = \phi_1 L + \cdots + \phi_1 L^p$ and the fractional differencing operator $(1 - L)^d$ (Hosking, 1981), as:

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{k-1-d}{k} \delta_{k-1}(d) L^k \text{ with } \delta_0(d) = 1.$$

3.3 Joint copula models

To examine the tail dependence structure, we have used three copula models viz. the Gaussian, Student-t and Clayton copulas. The performance of the copula models has been compared with the use of information criteria of AIC and BIC. The bivariate distribution function of the models has the following forms:

- Gaussian copula:

  $$C(u, v; \tau) = \varphi_\rho \left(\varphi^{-1}(u), \varphi^{-1}(v); \tau\right)$$

  where the variables $u, v \in [0, 1]$ are the cumulative distribution functions of the standardised residuals from the marginal distributions. φ_ρ is the bivariate distribution representing normal function with the linear association defined by τ, and φ^{-1} is the inverse function of the univariate distribution function.

- Student t-copula:

  $$C(u, v; \tau) = t_{v,\tau} \left(t_v^{-1}(u), t_v^{-1}(v)\right)$$

  where the variables $u, v \in [0, 1]$ are the cumulative distribution functions of the standardised residuals from the marginal distributions. $t_{v,\rho}$ is the bivariate distribution representing Student-t distribution with degrees of freedom (DoF) with the linear association defined by τ, and t^{-1} is the inverse function of the univariate distribution.

As the stock markets downward trend together in extreme events indicating a positive lower tail dependence with different behaviours in the extreme right indicating zero upper tail dependence. As the stock markets have uncertain features during extreme events, we require to be flexible in modelling the tail dependence. We have chosen Clayton copula from the Archimedean family to capture the wide range of dependence structure with desirable properties such as symmetry and associativity.

- Clayton copula:

  $$C(u, v; \theta) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta}$$

  where the dependence parameter $\theta \in (0, \infty)$. The marginal becomes independent with θ approaching zero.

4 Results and discussion

We present the analysis of the tail dependence analysis using FIGARCH-Copula approach of the major equity traded equity markets of Asia in this section. Section 4.1 presents the descriptive statistics and the time series plot to support visualising the data. The return series have also been examined the stationarity using augmented Dickey-Fuller (ADF) test and the auto-correlation function (ACF) plots. Section 4.2 presents the estimates of FIGARCH model along with the residual diagnostics. The best fit marginal distributions have been evaluated on the basis of the minimum AIC and the BIC values. Finally, Section 4.3 presents the copula distributions to examine the tail dependence structures in the equity markets of Asia.

4.1 Preliminary analysis

Table 1 presents the descriptive analysis of all returns of equity market data considered for the study. Table 1 shows all the mean, maximum, minimum, standard deviation (measures of dispersion), skewness, and kurtosis (measures of shape) of the data. The normality test has also been presented with Jarque-Bera (JB) statistics and the significance values. It has been observed that the average returns are around 0.03% or all equity markets with minimum average returns in SHANGHAI and maximum in NIFTY. NIFTY index of India has also shown some extreme observations in comparison to other equity markets of India. The minimum of around –13% and a maximum of 8% returns are seen in the NIFTY time series data. NIFTY index has also shown higher deviations from the normal skewness and kurtosis. The skewness different from zero and excess kurtosis of all return series indicates that the time series are not normally distributed. The results of the JB test value are found significant in all-time series that strongly rejects the hypothesis that time series are normal.

Table 1 Summary statistics

Statistic	*HANG SENG*	*SHANGHAI*	*KOSPI*	*NIKKEI*	*NIFTY*
Mean	0.00030	0.00017	0.00041	0.00047	0.00052
Maximum	0.04924	0.05542	0.07180	0.07731	0.08400
Minimum	–0.05720	–0.08039	–0.08766	–0.08252	–0.13903
Std. dev.	0.01470	0.010842	0.01080	0.01223	0.01164
Skewness	–0.45779	–0.63258	–0.59048	–0.35049	–1.60622
Kurtosis	2.25861	6.04020	8.08737	6.75190	25.24070
Jarque-Bera	67.66214	528.6178	1329.706	710.1979	24,617.21
Sig.-value	0.000	0.000	0.000	0.000	0.000

Figure 1 presents the time series plot of daily returns of equity markets of Asia. We observed the higher volatility of returns in the early months of the year 2020 with the nationwide lockdown in the countries to arrest the spread of novel coronavirus (COVID-19). Clearly, the plot depicts highly recognisable volatility, which supports our choice for using GARCH for modelling the univariate margins. We have carried out ADF test of stationarity to test the null hypothesis that the time series are non-stationary. Table 2 shows the results of unit root test, which clearly indicates that all return series are with no differencing, i.e., $I(0)$. The ACF plots are a graphical summary of all return series to see the strength of association of observation in the time series with its lagged values (see Figure 2). The non-significant serial correlations at various lags greater than 1 indicate stationarity in the data.

Figure 1 Time series plot of Asian market index returns (see online version for colours)

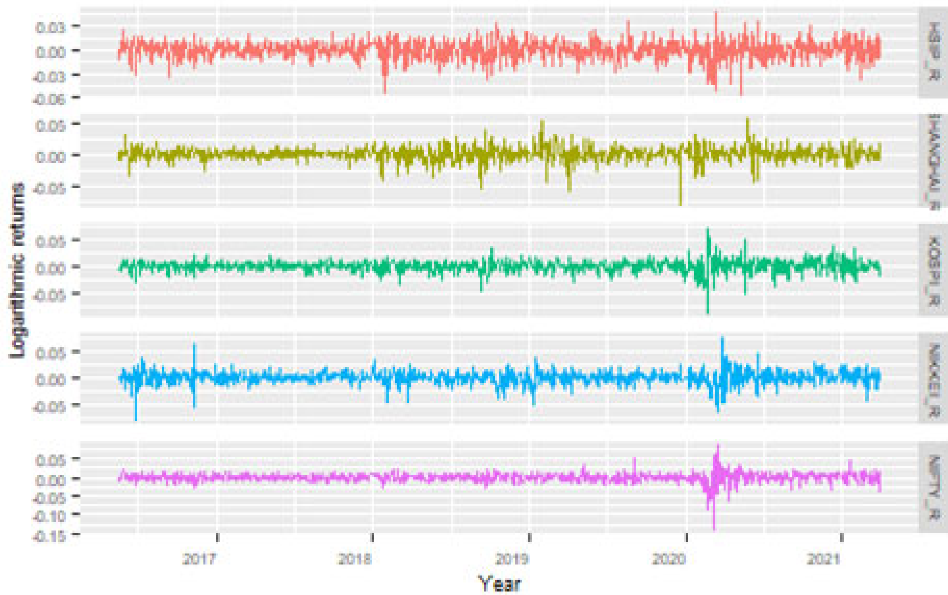
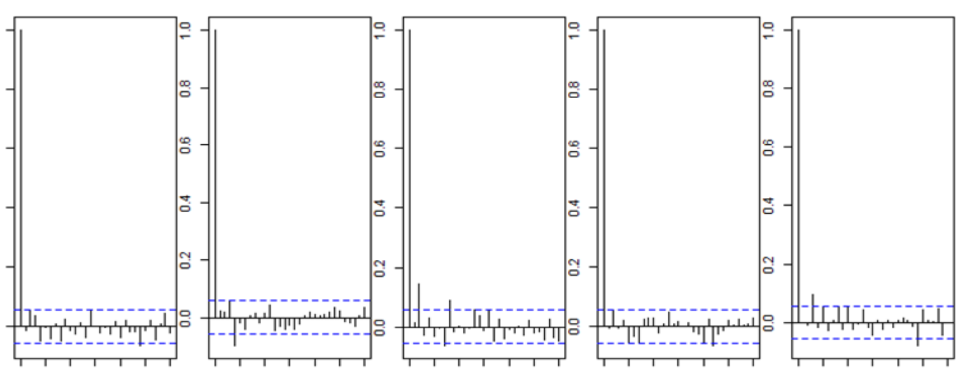


Table 2 Unit root tests (ADF test)

	ADF test statistic	*Critical value 'τ' (1%)*	*Sig. value*	*Integration level*
HANG SENG	23.10	2.58	$P < 0.01$	$I(0)$
SHANGHAI	23.41	2.58	$P < 0.01$	$I(0)$
KOSPI	20.77	2.58	$P < 0.01$	$I(0)$
NIKKEI	22.92	2.58	$P < 0.01$	$I(0)$
NIFTY	24.23	2.58	$P < 0.01$	$I(0)$

Figure 2 ACF of Asian market index returns (see online version for colours)



4.2 FIGARCH estimation of marginal distributions

We analyse the volatility of the returns using GARCH functions, which can offer to estimate univariate GARCH-type time series models in the conditional variance and ARMA specification in the conditional mean. The models can be estimated with the maximum log-likelihood approach underlying different assumptions, normal, Student-t, and GED errors. The residual diagnostics like Ljung-Box (LB) statistics and ARCH LM of homoscedasticity have been performed to ascertain the fitness of the estimate of parameters.

Table 3 Estimated coefficient of the FIGARCH model

Parameters	*HANG SENG*	*SHANGHAI*	*KOSPI*	*NIKKEI*	*NIFTY*
μ	0.0008 (0.002)	0.0004 (0.051)	0.0008 (0.000)	0.0008 (0.000)	0.0009 (0.000)
ω	0.0000 (0.311)	0.0000 (0.286)	0.0000 (0.314)	0.0000 (0.000)	0.0000 (0.198)
α_1	0.0432 (0.000)	0.0563 (0.000)	0.1060 (0.000)	0.1673 (0.000)	0.1019 (0.000)
β_1	0.9470 (0.000)	0.9377 (0.000)	0.8679 (0.000)	0.7780 (0.000)	0.8728 (0.000)
Shape	1.3720 (0.000)	4.0062 (0.000)	1.1844 (0.000)	4.2191 (0.000)	1.3923 (0.000)
LB test (no serial correlation)	0.5392 (0.462)	1.5070 (0.219)	0.1900 (0.662)	0.7065 (0.790)	4.764 (0.069)
ARCH LM test (presence of homoskedasticity)	0.5771 (0.447)	0.8791 (0.348)	0.2267 (0.634)	0.0047 (0.945)	1.244 (0.264)

Table 4 AIC criterion of marginal distributions

	Normal		*Student 't'*		*Generalised error distribution (GED)*	
	AIC	*BIC*	*AIC*	*BIC*	*AIC*	*BIC*
HANG SENG	–6.205	–6.187	–6.240	–6.218	*–6.241*	*–6.219*
SHANGHAI	–6.373	–6.356	*–6.499*	*–6.477*	–6.492	–6.470
KOSPI	–6.521	–6.504	–6.594	–6.573	*–6.597*	*–6.575*
NIKKEI	–6.198	–6.181	*–6.295*	*–6.273*	–6.291	–6.283
NIFTY	–6.568	–6.550	–6.295	–6.273	*–6.606*	*–6.584*

Table 3 present the FIGARCH estimation of daily returns from equity markets under consideration for the study. The models have been estimated with the best-fit approach using minimum AIC value for the different assumptions of normal, Student-t and GEDs (Table 4). The results indicate that Student-'t' best fits for the return series SHANGHAI and NIKKEI, while GED for the HANG SENG, KOSPI and NIFTY. The parameter estimates of FIGARCH have been evaluated with the underlying assumptions. The parameters μ, α_1, β_1, and the shape statistics are found significant ($p < 0.01$) in all-time series. The residual diagnostics have been done using ARCH LM for heteroskedasticity and LB test for serial correlation in the error term. The test statistics of ARCH LM of heteroskedasticity indicate that residuals of all the time series failed to reject the null hypothesis of presence of homoskedasticity. The serial correlation in residuals was tested using LB statistics, and the results show no serial correlation in residuals in all the time series.

Table 5 Copula results

Pairs	*Parameters*	*Gaussian copula*	*t-copula*	*Clayton copula*
NIFTY-HSPI				
Parameter(s)	ρ	0.16	0.13	0.29
	γ	--	3.71	--
Dependence measures	Γ	0.01**	0.09**	0.13**
	λ_l	0.00	0.12	0.00
	λ_r	0.00	0.12	0.09
Fit statistics	AIC	–13.39	*–26.58*	–20.76
	BIC	–8.33	*–16.45*	–15.70
NIFTY-SHANGHAI				
Parameter(s)	ρ	0.06	0.05	0.12
	γ	--	4.76	--
Dependence measures	Γ	0.04	0.03	0.06
	λ_l	0.00	0.06	0.00
	λ_r	0.00	0.06	0.00
Fit statistics	AIC	–0.25	*–6.11*	–2.97
	BIC	4.82	*4.02*	2.10
NIFTY-KOSPI				
Parameter(s)	ρ	0.10	0.05	0.24
	γ	--	2.00	--
Dependence measures	Γ	0.06	0.03	0.11
	λ_l	0.00	0.20	0.00
	λ_r	0.00	0.20	0.06
Fit statistics	AIC	–1.02	*–72.26*	–9.47
	BIC	4.05	*–62.13*	–4.40
NIFTY-NIKKEI				
Parameter(s)	ρ	–0.13	–0.05	–0.5
	γ	--	2.00	--
Dependence measures	Γ	–0.09	–0.03	–0.2
	λ_l	0.00	0.17	0.00
	λ_r	0.00	0.17	0.00
Fit statistics	AIC	–0.77	*–103.63*	–26.21
	BIC	4.29	*–93.5*	–21.14

Note: ρ correlation coefficient, γ degree of freedom, Γ Kendall's tau, λ_l upper tail dependence, λr lower tail dependence, 'AIC' Akaike information criterion and 'BIC' Bayesian information criterion.

4.3 Copula distribution

We transformed the standardised residuals to obtain the uniform marginals on the unit interval using the best-fitted marginal distributions based on minimum AIC and SIC values. The copula distributions are estimated based on these uniform marginal distributions. The present study has computed the parameter estimates, dependence measures, and the fit statistics for the Gaussian, Student-t and Clayton copula (Table 5). We find t-copula performs better than the other two copula functions on the basis of minimum AIC and BIC values. The findings are consistent with the work of Cossin et al. (2010) and Du and Lai (2017). The positive values of the dependence measures indicate the existence of the relationships during extreme events. NIFTY-KOSPI pair has shown the highest positive upper and lower tail dependences, followed by NIFTY-NIKKEI. The dependence measures values were lowest with SHANGHAI.

Overall, the results indicate that Asian markets exhibited a high dependence during extreme events. The results are in contrast to the findings of Sehgal et al. (2018), which claim a low level of integration in the Asian equity markets. The study was carried out on a sample period 2004–2015, however the period of COVID pandemic 2020–2021 is imminently important as considered in the study. Cai et al. (2017) examination of Asian stock markets shows that compared to the upper tail, the lower tail exhibit stronger dependence, and the conditional tail dependence of China vis-à-vis other countries is zero. Some authors have also emphasised trading volumes, though even after incorporation of lagged effects of volumes, persistence has been observed in major markets (Chen et al., 2001). Ning and Wirjanto (2009) have established a strong upper tail dependence between volume and stock returns of East Asian stock markets using GARCH copula estimations. However, Naeem et al. (2014) find a weak upper tail dependence between return and volume for Hong Kong and Indian stock indices, and leverage effect has been seen for Malaysia and Indonesia stock indices due to high volumes. The work of Duppati et al. (2017) establishes that China and Singapore have the largest differencing parameter. The non-parametric copula analysis of ASEAN markets by Duong and Huynh (2020) shows the need for adequate diversification to avoid contagion effects. A recent study by Mishra and Mishra (2020) established that during the pandemic, the investment sentiment weakens, generating a spiral of market uncertainty leading to volatility clustering across the Asian stock markets. We, therefore, derive that during extreme events, the major Asian stock markets, in general, exhibit strong upper and lower tail dependence, thus implicating the need for diversification to avoid risk aggregation.

5 Conclusions

Tail dependence structure across financial markets is of special relevance to investors and analysts. Researchers have observed that various financial markets, especially stock markets, exhibit tail dependence and patterns of volatility clustering. High correlations at tails imply risk aggregation. The problem is more severe during extreme events. A variety of approaches have been deployed by researchers to examine the phenomenon of volatility clustering using a host of models, particularly GARCH family models. In this paper, we have used the FIGARCH model to examine the volatility patterns and relationships across major Asian stock markets during the period April 2016 to March

2021. Results show that Asian markets exhibited a high dependence during extreme events. We have supplemented the results with copulas to find the tail dependence. During the extreme events, we find that major Asian stock markets exhibit significant tail dependence. Our results carry important implications for portfolio investors and risk managers to portfolio investors and risk managers to respond to inadequate diversification in these markets. The policymakers should frame appropriate strategies and intervene in markets to protect investors without compromising market efficiency. An extension of this research can be the analysis of high-frequency data in stock markets around extreme events for market risk assessment under the assumptions of dynamic specification of the copula-FIGARCH model.

Data availability

The data used for the study is available in the public domain on the website yahoo.com.

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