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Dynamic dependencies and return connectedness among stock, gold and Bitcoin markets: Evidence from South Asia and China

JEL Classification: F30; F37; G15

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Abstract

Research background: In order to examine market uncertainty, the paper depicts broad patterns of risk and systematic exposure to global equity market shocks for the major South Asian and Chinese equity markets, as well as for specific assets (gold and Bitcoin).

Purpose of the article: The purpose of this paper is to investigate the dynamic correlation among the major South Asian equity markets (India and Pakistan), the Chinese equity markets, the MSCI developed markets, Bitcoin, and gold markets.

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Methods: While applying the GARCH-Vine-Copula model and the TVP-VAR Connectedness approach, major patterns of dependency and interconnectedness between these markets are investigated.

Findings & value added: We find that risk shocks from developed equity markets are critical in these dynamic links. A net return spillover from Bitcoin to the Chinese and Pakistani stock markets throughout the sample period is reported. Interestingly, gold can be applied to hedge and diversify positions in China and major South Asian markets, particularly following the COVID-19 outbreak. Our paper presents three main original add valued: (1) This paper adds global factors to the targeted study of risk transmission among South Asian and Chinese stock markets for the first time. (2)The assets of Bitcoin and gold were added to the study of risk transmission among South Asian and Chinese stock markets for the first time, enabling the research in this paper to observe the non-linear link among the South Asian and Chinese stock markets with them. (3) Our research adds to these lines of inquiry by giving empirical evidence on how COVID-19 altered the dependent structure and return spillover dynamics of Bitcoin, gold and South Asian and Chinese stock markets for the first time. Our results have critical implications for investors and policymakers to effectively understand the nature of market forces and develop risk-averse strategies.

Introduction

As the world becomes increasingly financially integrated, linkages between global financial markets are becoming more assertive. Inter-market correlations have traditionally been a significant focus of academic research. The investigation of correlations between financial markets is of great significance for inter-market volatility spillovers, risk transmission, and asset allocation (Natarajan *et al.*, 2014). In the wake of the 2008/09 Global Financial Crisis (GFC) and the recent healthy crisis of COVID-19, the study of market spillovers and contagion risk has grown considerably in importance along with the huge concerns about systemic risk among various market participants (e.g., Wu *et al.*, 2021). Spillovers are measured quantitatively through connectedness, as it is an important indicator of correlation between market factors (Diebold & Yilmaz, 2012; 2014). A high degree of connectedness between networks of variables undoubtedly facilitates the rapid propagation of systemic risk, especially during crises (Benoit *et al.*, 2017).

In this study, each market is considered a portfolio asset (a node in network), and the global stock markets are considered a common factor among systematic risk factors. China and India are among the world's fastest-growing emerging economic countries, and their relationship is profoundly antagonistic and cooperative. At the same time, Pakistan and the other major country in South Asia, has a relationship with China and India at opposite extremes. China is currently the world's second-largest econo-

my, while India is the world's sixth-largest economy (IMF, 2021) and has maintained high growth rates. Pakistan and India are vital countries and major economies in South Asia and are critical members of the South Asian Free Trade Area (SAFTA). However, political challenges, such as the India-Pakistan conflict, will continue to stymie regional economic cooperation in South Asia (Huda & McDonald, 2016). In addition, China was India's top trading partner, but the US has overtaken it in 2021 (Panda, 2021). And India is China's biggest South Asian trading partner. In recent years, China has worked with Pakistan on large projects (China-Pakistan Economic Corridor), which has become the Belt and Road's core and flagship project. Pakistan's economic reliance on China has risen. At the same time, as the earliest released and the largest market capitalized asset in the cryptocurrencies market, Bitcoin is quickly becoming a focus of attention for traders seeking more speculative opportunities and investing in alternatives (Dyrberg, 2016). As the most mature cryptocurrency asset in the cryptocurrency market, the examination of Bitcoin can serve as a vane for the research of cryptocurrencies (Cohney *et al.*, 2019; Zhang *et al.*, 2020).

This research uses the Vine-Copula approach and the TVP-VAR connectedness approach to study the dependency structure and return spillover effects of China, major South Asian stocks, gold and Bitcoin during the period 2015–2021, and further analyses the dependency structure of risk spillovers from these markets during COVID-19.

Our research contributes to the existing literature in three parts. This paper adds global factors to the targeted study of risk transmission among South Asian and Chinese stock markets for the first time. The influence of developed market on Asian stock markets is becoming increasingly significant (Burdekin & Siklos, 2012). There is no doubt that the trend towards globalization will lead to a significant increase in global stock market linkages and closer potential spillover effects. However, the jury is still out on whether major South Asian stock markets are connected to global risk factors, and existing studies only suggest that the high correlation between stock markets in East and Southeast Asia is mainly due to common global market factors (Chen, 2018). Thus, this will be among the first studies to contribute to the existing literature by assessing the dynamic dependence structure and return transmission channels of major South Asian stock markets, as well as Chinese stock markets, and MSCI developed market indices.

Meanwhile, the assets of Bitcoin and gold were added to the study, enabling the research in this paper to observe the non-linear link among the stock market with Bitcoin and gold. These two assets in this region are beneficial for investors to construct portfolios to hedge against extreme stock market risks and has implications for policymakers to identify systemic risks. Despite becoming an increasingly popular and sought-after asset, decentralized, decentralized-driven cryptocurrencies are gradually being brought under the purview of national financial regulation. The maturation and development of cryptocurrencies will create new shocks to the effectiveness of unconventional monetary policies, especially during financial crises where standard asset prices fluctuate sharply. Our research also looks at how to support the financial system and prevent cryptocurrency bubbles from bursting to prevent economic shocks. In previous works, most studies have focused on oil or have used the US stock market as a proxy for developed markets (Sarwar *et al.*, 2020), and studies on the South Asian region have been far less specific than the variables we use (Bitcoin and gold), thus feeding back more specific information that investors want, especially those interested in cryptocurrencies.

Finally, our research adds to these lines of inquiry by giving early empirical evidence on how COVID-19 altered the return spillover dynamics of various assets. COVID-19 (SARS-CoV-2) is a severe acute infectious disease that was discovered in late 2019 and has since spread globally, resulting in a major pandemic that has become one of the deadliest in human history. Despite the fact that the body of literature on the financial and economic impact of the COVID-19 has grown rapidly (e.g., Aslam *et al.*, 2022; Mazur *et al.*, 2021), the research focus is scattered and our topic, in particular has not yet been addressed.

The paper is organized as follows. Section 2 provide a brief literature review. Section 3 presents the methodology and dataset. Section 4 analyzes major empirical results and Section 5 discusses the important findings. Section 6 outlines the conclusions and implications of the paper.

Literature review

While it is commonly considered that developed nations exert impact on Asian financial markets through finance costs, portfolio rebalancing and risk appetite channels, China primarily influences regional economies

through critical trade links (Arslanalp *et al.*, 2016). Of the sparse studies on South Asian and Chinese stock markets, most are included under other thematic frameworks, such as BRICS (acronym for five leading emerging economies: Brazil, Russia, India, China, and South Africa) or energy markets, and there is a lack of targeted research. Jebran *et al.* (2017) discover that Chinese and Indian stock markets have significant two-way volatility spillovers after the GFC, while Pakistani and Indian stock markets have two-way volatility pre-GFC spillovers, leaving only a unidirectional volatility spillover from Pakistan to Indian stock markets after the crisis. The findings obtained by Kumar and Dhankar (2017) conclude that the Indian-Pakistan's stock market is highly integrated, but insensitive to fluctuations in international markets. According to Shehzad *et al.* (2021), the volatility spillover among the KSE (Karachi Stock Exchange of Pakistan) and SSEC (Shanghai Stock Exchange) is minimal during steady times. During the COVID-19 pandemic, however, there is a strong unidirectional volatility spillover from SSEC to the KSE index.

Bitcoin is a specific virtual commodity that is not released by a monetary authority and has no monetary properties such as legal tender (Baur *et al.*, 2018). Bitcoins are based on algorithms. Proponents believe that their actual value derives from rule certainty, scarcity, anonymity, global circulation. At the same time, critics argue that Bitcoins have neither the intrinsic value of the gold standard nor the sovereign credibility of fiat money behind them and lack the backing of actual economic activity and proper security safeguards (Dorofeyev *et al.*, 2018). Given these insights, and despite some controversial elements, the volatility of Bitcoin's price has attracted the interest of many investors, and the cryptocurrency market is expanding. The explosion of Bitcoin has raised awareness among stakeholders of the importance of decentralized currencies.

The recurring volatility in equity markets poses a significant risk to equity investments (Ghazali *et al.*, 2020). China is the world's largest gold producer (World Gold Council, 2020) and the world's cryptocurrency mining hub, accounting for approximately two-thirds of global production and holding the world's most enormous Bitcoin hash rate (Chainalysis, 2020). The South Asian markets, and India in particular, are also one of the largest markets for gold and Bitcoin (Chainalysis, 2020; World Gold Council, 2021), indicating that both the Chinese and South Asian markets are strongly connected to Bitcoin as well as gold. In a previous study, Dyhrberg (2016), using an asymmetric GARCH model, found that Bitcoin has several

of the hedging properties of gold. It can act as a hedging instrument for equities. But in contrast, Klein *et al.* (2018) find that gold is a high-quality safe haven asset during periods of market turmoil, while bitcoin is positively correlated with downside markets. Their research concludes that bitcoin does not reflect any of gold's unique properties. Jain and Biswal (2016) observe that the negative correlation between the Sensex and the gold price in India is mutually caused. A fall in the gold price causes the Sensex (BSE Sensex index) to fall, but a fall in the Sensex causes the gold price to rise. Mensi *et al.* (2018) discover no evidence of co-movement between the Chinese and Indian stock markets and gold, implying that gold might be utilized as a hedge or safe-haven asset in the face of dramatic market swings in China and India. According to Kyriazis (2020), Bitcoin is a good hedge against stock market indexes, but not as good as gold. Bitcoin and gold may have an asymmetric and nonlinear relationship. According to Pho *et al.* (2021), gold is a better portfolio diversifier than Bitcoin, and Bitcoin is more appropriate for risk-averse investors in China, but gold is more suitable for risk-averse investors. Wang *et al.* (2019) used the VAR-BEKK-GARCH framework and a Wald test to find that there was a two-way volatility spillover among Bitcoin and gold, and that Bitcoin could be used to hedge the Chinese stock market. However, the dynamic volatility between assets is time-varying, and we will present the latest volatility spillovers using a different sampling interval (2015–2021). In addition, Hung (2021) applies a wavelet transform framework to find that both Bitcoin and the stock market show signs of moderate integration. However, some studies suggest that Bitcoin is less effective than gold. However, previous researchers have provided no conclusive evidence of a correlation between Chinese and South Asian stock markets and Bitcoin. This is, therefore, a timely effort to undertake a scientific assessment and evidence-based discussions. Furthermore, the role of Bitcoin as a safe haven asset is closely related to other assets in the portfolio as well as economic cycles.

The Vine-Copula model is applied to characterize the dependency structure of paired assets, specifically the tail dependency structure. Tail dependence structures can be used to discuss asset class correlations in financial markets, such as whether an increase (or decrease) in the price of one market will cause an increase (or decrease) in the price of another market. Furthermore, the Kendall rank dependence structure investigates the consistency of price trends across markets, establishing a link between consistency and correlation measures (Hollander *et al.*, 2013). Our Vine-Copula

approach has an advantage over other studies that extensively use 2D Archimedes or Gaussian Copula (e.g., Syuhada *et al.*, 2021) in characterizing the nature of inter-market dependence, in that it can distinguish whether the inter-market dependence structure is conditional through that market or it is simply unconditional dependence (Goodwin & Hungerford, 2015). Based on the nature of the dependencies, investors can make useful portfolio adjustments. The Vine-Copula approach has gained popularity in recent years for showing high-dimensional risk dependencies in precious metals, cryptocurrencies and other markets (Sharma & Sahni, 2021; Talbi *et al.*, 2021).

Additionally, the copula approach has limitations. It focuses on the dependence of the variance-covariance matrix and does little to address the mean's dependence. In this regard, if we focus on the time-varying evolutionary characteristics of the relationships among assets, the time-varying parametric vector autoregression (TVP-VAR) approach may be considered (Antonakakis *et al.*, 2020). Unlike the copula technique, TVP-VAR can use a Bayesian interpretation to capture the time-varying features of the mean and variance matrices (Pham & Nguyen, 2021). We pay attention to time-varying measures of spillover along the connectedness axis of the TVP-dynamic VAR. We utilize the TVP-VAR method to overcome the drawbacks of connectedness estimates based on the variance decomposition of standard VAR models; outcome sensitivity due to arbitrary rolling window period selections, and observation loss due to rolling window analysis. Additionally, it enables the capture of the overall connectivity metric's dynamics as well as the structure of cross-asset connectivity. However, the disadvantage of TVP-VAR is that it does not account for the fat-tail characteristics of financial market returns (Barro, 2006). This is a critical limitation for our purposes, and thus the TVP-VAR connectedness approach is used in conjunction with the Vine-Copula approach in this paper.

There is limited literature on the linkages between commodity assets such as Bitcoin and gold and South Asian stock markets. Examining the systemic risk dependencies among these financial markets is of great significance for inter-market spillovers, risk transmission, and asset allocation. In particular, international institutions such as the International Monetary Fund (IMF) and the governments of the countries concerned should monitor the extent of linkages between China and South Asian economies and certain popular assets to design strategies aimed a macro prudence to di-

versify risk. As well as to maintain financial stability in the region in the presence of shocks of a global nature emanating from global market shocks.

Research method

Estimation of the marginal distribution

Historical data of stock market, commodity, and cryptocurrency returns frequently exhibit 'sharp peak and fat tail' and 'volatility clustering' characteristics. The GARCH model's characteristics have an excellent ability to explain such data; thus, it is well suited for estimating the marginal distribution (Zeng *et al.*, 2022). To eliminate the influence of autocorrelation and heteroskedasticity on the return data, we fitted the marginal distributions of the logarithmic daily return series of the markets with the AR(1)-GJR-GARCH(1,1)-*Skew-t* framework and extracted the residual series after noise reduction treatment. The model not only better captures the 'leverage effect' among markets, but it also effectively depicts characteristics of the paired markets' return series such as 'volatility clustering' and 'sharp peak and fat tail' (Glosten *et al.*, 1993; Zeng & Ahmed, 2022). The standardized residuals have a Skew-*t* distribution, as shown below:

$$\begin{aligned}
 r_t^i &= C_0 + C_1 r_{t-1}^i + e_{i,t} \\
 h_{i,t}^2 &= \omega_1 + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1}^2 + \gamma_i U_{t-1} e_{i,t-1}^2 \\
 e_{i,t} &= h_{i,t} \varepsilon_{i,t} \\
 \varepsilon_{i,t} &\sim \text{Skew Student's } t(v, \lambda)
 \end{aligned}
 \tag{1}$$

where r_t^i denotes the logarithmic returns of paired markets price, $\varepsilon_{i,t}$ is the standardized residual series, $h_{i,t}$ indicates the conditional volatility, and $e_{i,t}$ represents the residual. The mean of the model is set to be 0, the variance is 1, and U_{t-1} is the indicator function $U_{t-1} = \begin{cases} 1, & e_{i,t-1}^2 < 0 \\ 0, & \text{Others} \end{cases}$, $C_1, \alpha_i, \beta_i, \gamma_i, \omega_1$ is the parameter to be estimated for the model. And to achieve a better fit, a *skewed student-t* fit distribution is used for the standard residuals in the model.

Vine-Copula

With a small number of parameters, the copula is a useful probability distribution for describing complex multivariate interdependencies. Copula-based regression is a method of balancing the flexibility of regression models with parameter conservation that has received a lot of attention.

Given that the n -dimensional random variable vector function $X = (x_1, x_2, \dots, x_n)$, whose joint distribution has a density function of $f(x_1, x_2, \dots, x_n)$, then the conditional density function can be shown as:

$$f(x_1, x_2, \dots, x_n) = f_n(x_n)f(x_{n-1}|x_n) \cdots f(x_1|x_2, \dots, x_n). \quad (2)$$

Different setting $F_1(x_1), F_2(x_2), \dots, F_n(x_n)$ as the marginal distribution of x_1, x_2, \dots, x_n , there exists a Copula function C such that $F(x_1, x_2, \dots, x_n) = C\{F_1(x_1), \dots, F_n(x_n)\}$. The joint density function can be expressed as:

$$f(x_1, \dots, x_n) = c_{1\dots n}\{F_1(x_1), \dots, F_n(x_n)\}f_1(x_1) \cdots f_n(x_n) \quad (3)$$

where, $c_{1\dots n}(\bullet)$ is the probability density function of the n -dimensional copula.

An n -dimensional R-Vine structure consists of $n-1$ trees, let the set of all nodes on the first tree T_1 be set is $N_1 = \{1, 2, \dots, n\}$ and the set of all edges on T_1 is E_1 . The next $n-2$ trees, each node on tree T_i is a pair of variables on the T_{i-1} edge of the previous tree, i.e. $N_i = E_{i-1}$.

Given $X = (x_1, x_2, \dots, x_d)$, the joint probability distribution function of the d -dimensional R-Vine is:

$$f(X) = \prod_{k=1}^d f(x_k) \cdot \prod_{i=1}^{d-1} \prod_{e \in E_i} c_{j(e), k(e)|D(e)}(F(x_{j(e)} | x_{D(e)}), F(x_{k(e)} | x_{D(e)})) \quad (4)$$

where E_i is the set of edges, $e = j(e)$ and $k(e)|D(e)$ is an edge in E_i , $c_{j(e), k(e)|D(e)}(\cdot, \cdot)$ is the corresponding Copula function, $j(e)$ and $k(e)$ are the two conditional nodes connected to edge e , and $D(e)$ is the set of conditions. Aas (2009) introduced a particular framework for two famous vine-copula structures, C-vine and D-vine. For n -dimensional dependencies, the C and D-vine-copula functions are represented as:

C-Vine-Copula model:

$$f(X) = \prod_{k=1}^d f_k(x_k) \prod_{i=1}^{d-1} \prod_{j=1}^{d-i} c_{i,i+j|1:(i-1)} \left(F(x_i|x_1, \dots, x_{i-1}), F(x_{i+j}|x_1, \dots, x_{i-1}) \right) \quad (5)$$

D-Vine-Copula Model:

$$f(X) = \prod_{k=1}^d f_k(x_k) \prod_{i=1}^{d-1} \prod_{j=1}^{d-i} c_{j,j+i|(j+1):(j+i-1)} \left(F(x_j|x_{j+1}, \dots, x_{j+i-1}), F(x_{j+i}|x_{j+1}, \dots, x_{j+i-1}) \right) \quad (6)$$

The Vine-Copula model can generate three structures, C-Vine, D-Vine and R-Vine. The selection of the optimal Vine-Copula structure is determined by calculating the AIC value and BIC, as well as the Vuong statistic.

TVP-VAR-based dynamic connectedness approach

Diebold and Ylmaz (2009), Diebold and Ylmaz (2012), and Diebold and Ylmaz (2014) describe a widely used framework for estimating spillover in predefined networks using vector autoregressive (VAR; Sims, 1980) models. Antonakakis *et al.* (2020) extended the above framework by introducing a dynamic connectedness method based on time-varying parametric vector autoregression (TVP-VAR), with the outcome that the dynamics are independent of the rolling window size. Additionally, the TVP-VAR-based dynamic connectedness method has the following advantages: (i) it does not require an arbitrarily large rolling window size; (ii) it permits the variance-covariance matrix to estimate changes via the Kalman filter; (iii) it can be used with low-frequency data sets; and (iv) it avoids observation loss. The approach taken in this study is similar to that taken by Antonakakis *et al.* (2020) and Bouri *et al.* (2021). To be more precise, estimate the TVP-VAR (1) using the Bayesian Information Criterion (BIC), which can be summarized as the following equation:

$$\begin{aligned} x_t &= a_t x_{t-1} + \varepsilon_t & \varepsilon_t &\sim N(0, \varphi_t) \\ \text{vec}(\alpha_t) &= \text{vec}(\alpha_{t-1}) + \omega_t & \omega_t &\sim N(0, \gamma_t) \end{aligned} \quad (7)$$

where x_t , x_{t-1} and ε_t are $k \times 1$ dimensional vector and α_t are $k \times k$ dimensional matrices. $\text{vec}(\alpha_t)$ and ω_t are $k^2 \times 1$ dimensional vectors, whereas γ_t is a $k^2 \times k^2$ dimensional matrix.

Then, following Bouri *et al.* (2021) 's estimation steps, we estimated the H-step ahead (scaled) Generalized-Forecast-Error-Variance-Decomposition (GFEVD) framework (Koop *et al.*, 1996; Pesaran & Shin, 1998), while maintaining the GFEVD's variable ordering (Diebold & Ymaz, 2009). The first step in estimating the GFEVD spillover framework is to convert the TVP-VAR to its Wold representation theorem vector moving average (VMA) representation, represented as:

$$\mathbf{x}_t = \sum_{i=1}^p \mathbf{a}_{it} \mathbf{x}_{t-i} + \boldsymbol{\varepsilon}_t = \sum_{j=0}^{\infty} \boldsymbol{\rho}_j \boldsymbol{\varepsilon}_{t-j} \quad (8)$$

The scaled GFEVD was then normalized to the unscaled GFEVD, $\phi_{ij,t}^g(H)$, to bring the sum of each row to unity. Thus, $\tilde{\phi}_{ij,t}^g(H)$ to represent the effect of variables j on variables i , i.e. the prediction error variance share, which is defined as the pairwise directional connectedness from j to i . And The indicator is calculated in the following,

$$\begin{aligned} \phi_{ij,t}^g(H) &= \frac{\varphi_{ii,t}^{-1} \sum_{t=1}^{H-1} (\sigma_i' \rho_t \varphi_t \sigma_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} (\sigma_i \rho_t \varphi_t \rho_t' \sigma_i)} \\ \tilde{\phi}_{ij,t}^g(H) &= \frac{\phi_{ij,t}^g(H)}{\sum_{j=1}^k \phi_{ij,t}^g(H)} \end{aligned} \quad (9)$$

where, $\sum_{j=1}^k \tilde{\phi}_{ij,t}^g(H) = 1$, $\sum_{i,j=1}^k \tilde{\phi}_{ij,t}^g(H) = k$. And σ_i is a selection vector with a unity at the i th position and zero elsewhere. $\tilde{\phi}_{ij,t}^g(H)$ explains the effect of a shock to variable j on variable i .

Based on the GFEVD, we first calculate the total connectedness index, which is calculated by the following equation:

$$TCI_t = \frac{\sum_{j,i=1, j \neq i}^K \tilde{\phi}_{ji,t}^g(H)}{K} \quad (10)$$

If the indicator is relatively high, it indicates that the network is highly interconnected and that market risk is high as shocks to one variable affect other variables, whereas a low indicator indicates that the majority of variables are fairly independent of one another, implying that shocks to one variable do not result in adjustments to other variables, suggesting a low market risk. The combined effect of a shock to variable j on all other varia-

bles is then calculated represented as total directional connectedness to others, as:

$$TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ij,t}^g(H) \quad (11)$$

We calculate the sum of all other variables' effects on variable j , which is defined as total directional connectedness from others:

$$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ji,t}^g(H) \quad (12)$$

We calculate net total directional connectedness by subtracting total directional connectedness to others from total directional connectedness from others. This value indicates whether a variable is a net transmitter/receiver of shocks, as:

$$NET_{jt} = TO_{jt} - FROM_{jt} \quad (13)$$

Finally, as shown in the following equation, there is the net pairwise directional connectedness (NPDC) among variables i and j :

$$NPDC_{ij}(H) = \tilde{\phi}_{ji,t}^g(H) - \tilde{\phi}_{ij,t}^g(H) \quad (14)$$

A positive (negative) value for $NPDC_{ij}$ indicates that variable i dominates over (is dominated over) variable j .

Data

This research investigates the impact of the MSCI Global Market Index, the dynamics of the interconnections among China, the major South Asian stock markets, and the markets of gold and Bitcoin. We use data from the daily closing prices of the Bitcoin market (BTC), the MSCI developed market index (MSCI), China (CSI 300), Pakistan (KSE), India (BSESN), and the gold market (Gold). The reason India and Pakistan were chosen as the main markets in South Asia for this study is that China and India have been strategic rivals in South and East Asia, and China has developed close commercial and military ties with its Indian "counterpart" Pakistan (e.g., BBC, 2021). It is therefore of particular interest to examine the links between these markets. Non-common trading days are excluded due to the different trading hours of the different markets. The sampling period for this paper

is from 14 September 2015 to 30 March 2021, with 1,181 observations. Both gold and stock market data are taken from DataStream (<http://product.datastream.com/>) and Bitcoin data from the CoinDesk website (<https://www.coindesk.com/>). For the data smooth, logarithmic differencing was used to find the first order log-returns of the paired market price indices.

Results

The results of descriptive statistics are shown in Table 1. First, we consider market volatility. Markets with the highest standard deviations are observed to be Bitcoin, China's CSI, and Pakistan's KSE, while gold, MSCI and India's BSESEN have very low relative standard deviations. This means that these four markets are more volatile than gold and developed markets over the entire sample interval. The return series for all pairs of markets are left-skewed except for gold, where the return series is right-skewed. All paired markets have excess kurtosis greater than three. The Jarque-Bera test rejects the original hypothesis that the return series follows a normal distribution, suggesting that the return series of all markets is non-normal with "sharp peaks and fat tails." The Q(20) results show that the return series of all markets are autocorrelated. In contrast, The ARCH-LM result shows that the return series of all paired markets have a strong ARCH effect, so the volatility aggregation of the return series of all paired markets is significant and therefore suitable for modelling using the GARCH family model. The ADF test results indicate that the return series of all paired markets are smooth and do not give rise to pseudo-regression problems. We then plot the return series for each stock market over the sampling period in Figure 1. We can easily observe the volatility profile of each paired market over the sample period, with the most volatile period for each market undoubtedly being the early part of the COVID-19 outbreak in early 2020. Since the stock market returns have significant non-normal characteristics and volatility clustering effects, the article uses the AR(1)-GJR-GARCH(1,1)-Skew-t model to further characterize the stock market return data. The first-order autoregressive model AR(1) is commonly used in financial data correlation analysis to eliminate the autoregressive properties of the sample data. In contrast, the leverage effect, heteroskedasticity, and volatility aggregation characteristics of the sample data can be better fitted using the GJR-

GARCH(1,1) model. Finally, the Skewed Student-t distribution (Skew-t) is used to characterize the standardized residuals, reflecting the presence of “spikes”, “thick tails”, and “skewed” characteristics. Furthermore, in Figure 1, we find dramatic volatility in both markets in the early 2020 (corresponding to the COVID-19 outbreak), which justifies our further analysis of the COVID-19 period.

Table 2 introduces the estimates and test results of the marginal distribution parameters for the return series for each market. We observe that most of the parameters are significant. Our particular interest is that the leverage coefficient γ for the BTC markets is less than 0. Therefore, it can be judged that the BTC market has a strong leverage effect, which is manifested by the fact that the impact of positive news is significantly more important than that of negative news. The Skew-t distribution of the standard residuals with the skewness parameter λ and the degrees of freedom parameter ν is both highly significant and statistically significant at the 1% confidence level. Therefore, the hypothesis that all return series obey a normal distribution is rejected, in line with the previous descriptive statistics, suggesting that return series in all markets have non-normal characteristics such as 'skew' and 'fat and peak tails'. At the same time, the p-values of the Kolmogorov-Smirnov tests are all significantly greater than 0.05. We can identify that the conditional marginal distribution obtained from the AR(1)-GJR-GARCH(1,1)-Skew-t model estimation and that the residual series obtained after the probability integral transformation (PIT) obeys the U(0,1) uniform distribution. We see an identical independent distribution in this case. We note that the residual sequences obtained after the probability integral transform (PIT) denotes an independent and homogeneous U(0,1) distribution. This meets the requirements of the Copula family modelling. We then apply the maximum spanning tree (MST) algorithm to select the optimal vine-copula dependence structure for the paired markets.

We first estimate the structure of the Vine-Copula based on the Maximum Spanning Tree algorithm. After determining the relevant structure of the Vine-Copula, we choose an optimal pair-copula function for each edge in the tree to be able to characterize the dependency structure between the random variables. We identify the optimal vine structure mainly by the values of AIC, BIC criterion and likelihood ratios. We also used the Vuong test to compare and pair models two-by-two. According to Table 3, the values for AIC and MLE show R-Vine as the optimal structure, and the optimal result for BIC shows D-Vine. The Vuong test results in Table 4 in-

dicating that the difference between the two is not statistically significant, as the p-values for all three vine structures are positive. However, because the statistics values are all positive, we prefer the R-Vine structure. In summary, the C-Vine structure is the aptest portrayal of the six paired market interdependencies.

According to Table 5, the tree 1 illustrates the unidirectional correlations between markets. The correlation structure of the paired markets exhibits dispersion in terms of node orders over the sample period (R-Vine structure). There is a strong lower-tail correlation (0.19), but no upper-tail correlation, between CSI and MSCI, implying a strong correlation between these two markets during market declines but not during rallies. In response to adverse shocks, we can assume a higher probability of extreme downside. As a result, caution should be exercised when constructing a diversified portfolio to avoid the risk-averse portfolios described above. The same situation exists for the CSI-KSE, and special attention should be paid to these markets' volatility in order to mitigate volatility transmission and risk transfer between markets. The Indian stock market has the strongest unconditional correlation with developed market indices (Kendall's $\tau = 0.25$). The upper tail correlation coefficient between the BSESEN-MSCI indices is larger than the lower tail dependent coefficient, implying that volatility caused by positive shocks is more significant than volatility caused by negative shocks. Meanwhile, gold has weak unconditional positive correlations with the Chinese stock market and Bitcoin (Kendall's $\tau = 0.04$ and 0.03 , respectively), but the tails are asymptotically independent, indicating that gold and these markets are not inextricably linked.

When conditional markets are included at the second level of the tree structure, the tail correlations among the Chinese market and the other markets exhibit asymptotically independent structures. Additionally, the conditional correlation between the CSI and the BSESEN is Kendall's $\tau = 0.13$, indicating a low correlation, and the developed market indices function as conditional markets. There are weak conditional correlations between the KSE and MSCI, Gold and the KSE, and the CSI and BTC, and all of them exhibit a Student's t distribution with equal upper and lower tail coefficients but asymptotically independent tails (tail dependence coefficients close to zero). We can conclude that as more conditional markets become known, the correlation between them decreases, implying that the unconditional dependent is significantly larger than the conditional dependent coefficient.

Starting from the 3rd level of the tree, we can find that with the inclusion of more than two conditional markets, all markets show an asymptotically independent conditional correlation structure (Kendall's τ close to 0) and a weak tail correlation (both upper and lower tail coefficients close to 0). We can conclude that the conditional correlation coefficients fall more significantly after the inclusion of conditional markets, suggesting that the inclusion of conditional markets acts as a diversifier of risk between markets. Investors should be mindful when constructing diversified portfolio choices that asset correlations are critical in verifying how assets interact with each other and the strength of the interconnections. According to the diversification principle, investing in less correlated assets reduces the likelihood of investment losses.

The significant point of the Copula method is that it can consider the tail risk relationships and dependent structure between variables, but it cannot help to understand the return spillover transmitters (receivers) that a particular variable plays within the sample period. Nor can it help us to understand the time-varying relationship and total connectedness over the sample period. Therefore, we will use a TVP-VAR based connectedness approach to fill these gaps in the next part.

We show the results of dynamic connectedness applying the TVP-VAR approach in Table 6, which enables us to discover the specifics of return spillovers among the system and individual financial assets. This section includes various measures of return connectedness for the sampled paired markets. We can see from these preliminary results that the TCI is 21.65%, demonstrating that the influence of all other financial assets accounts for 21.65% of the forecast error variation of one financial asset, indicating few financial asset connectedness. Also, based on the study of the time-varying relationship of TCIs in Figure 2, we can see that the magnitude of connectedness reached its highest level (close to 50%) during COVID-19 (early 2020). When comparing the degree of connectedness that exists in market states, we note that the high level of connectedness is more pronounced during COVID than before the COVID-19 outbreak. Meanwhile, market fears arising from the US-China trade war in mid-2018 also led to the TCI breaching 30%. In short, these markets are less connected in crisis-free periods than in crisis periods. The MSCI Developed Markets Index is the largest average contributor to the system (38.05%), followed by the Indian market (28.55%) and finally the Pakistan market (14.47%). The above information also comes to a clear conclusion in the examination of Figure 3.

The MSCI Developed Markets Index has the most significant degree of time-varying transmission when compared to all other markets. Following that, we investigate the system's net return connectedness, which captures the difference between transmitted and received shocks for each financial asset when the entire network is considered. In Table 6 and Figure 4, we concentrate on the system's net total connectedness. We observe that the MSCI index and the Bitcoin market are net shock transmitters during the entire study period. Our results concur with those of Abbas *et al.* (2013), who found that developed market return spillover to South Asian and Chinese markets as a result of their market size and importance in the global financial system. Throughout this time period, the MSCI index served as an excellent hedge against other market risks. There is evidence that BTC's role as a net shock transmitter is closely related to people's fears and risk appetites in the aftermath of the crisis outbreak (Chen *et al.*, 2020). However, it is important to highlight that in Figure 4, BTC becomes a net receiver of return after the COVID-19 outbreak. Interestingly, we observe that the Pakistan market, gold market, and CSI index have been net receivers throughout the COVID-19 outbreak. One potential explanation for gold's becoming free of return spillover could be that the outbreak of COVID-19 could lead to investors' closing out their positions, resulting in a large demand for cash (Umar *et al.*, 2021).

By analyzing risk spillovers and their spatial linkages, systemic risk can be managed more effectively (Blasques *et al.*, 2016; Gong *et al.*, 2019). Next, we use network diagrams to identify the sources of risk spillover shocks and the direction and intensity of return shocks transmitted (received) by the market in the system, which is also a visualization initiative for the results of the spillover structure of the paired markets in Table 6. Figure 5 shows a network diagram of the pairwise directional connectedness of the network for the TVP-VAR connectedness approach. The nodes in the network diagram are the six paired markets we have studied. To visualize the main nodes, we use the absolute values in the "NET" row in Table 6 to indicate the size of the nodes. Red nodes indicate net spill receivers and green nodes indicate net spill transmitters. The arrows indicate the direction of the overflow. The thicker the line connecting the nodes, the stronger the volatility spillover effect.

Our findings, in general, can assist investors in developing successful portfolio diversification and risk management techniques. Portfolio managers, for example, can utilize net pairwise connectedness across asset clas-

ses to compute hedging ratios and appropriate weights for diversified portfolios.

Further analysis: during COVID-19 period (23/01/2020–30/03/2021)

Financial markets as a system are inextricably linked to their various subsystems. When a financial crisis occurs, the increased volatility spillover effect frequently causes the financial crisis to spread rapidly from one market to another, resulting in a contagion effect and a cascade of other factors resonating to increase market-wide investment risk and create systemic risk (Bekiros, 2014; Kim *et al.*, 2015; Lu & Zeng, 2022). COVID-19 was a significant crisis event, resulting in unprecedented volatility and changes in the correlations between financial markets, necessitating adjustments to risk management strategies and portfolio asset structures. As a result, our subsequent analysis examines the correlation among the COVID-19 crisis and the sample markets, assessing the extent of crisis contagion between the sample markets and the correlation structure of the paired markets following the COVID-19 crisis. Our subsequent analysis will cover the period 23 January 2020 to 30 March 2021. On 23 January 2020, Wuhan, the city where COVID-19 is primarily found, implemented the world's first COVID-19 lockdown (BBC, 2021; Zeng & Lu, 2022).

To emphasize the most important findings and conserve space, we have omitted results from the marginal distributions, beginning with Vine-Copula. Following the COVID-19 outbreak, R-Vine results are presented in Table 7, revealing a significant shift in the dependence structure among the full-period paired markets.

According to the results of Table 7, there is no upper tail dependence for CSI 300-KSE at the first level of the tree, but there is a significant lower tail dependence (0.29). This implies that during bear markets, these two markets may appear to fall in lockstep. Separate portfolios comprised entirely of these two markets should be avoided in a portfolio, as the probability of loss is extremely high. This also reflects Pakistan's economy's high reliance on China. Petry (2022) argues that China has invested more than US\$60 billion in Pakistan to develop roads, energy projects, technology diffusion, and economic zones in order to create industrial zones and advance Pakistan's infrastructure, and that the slowdown in Chinese projects following the outbreak of COVID-19 has resulted in job losses and a decline in GDP, affecting investors' risk appetite. In comparison, the BSESN-MSCI exhibits

a moderate degree of dependence (Kendall' $\tau = 0.33$), with the upper tail dependence coefficient (0.28) being larger than the lower tail dependence coefficient (0.20). Portfolios comprised entirely of these two markets were more likely to earn returns over the sample period. This also demonstrates that, as South Asia's largest emerging market and the most open economy, India remains inextricably linked to developed markets following the COVID-19 outbreak. There is no tail correlation for CSI 300-BTC elsewhere, but a weaker correlation exists (Kendall' $\tau = 0.16$).

From the second tree onward, the majority of market portfolios exhibit asymptotically independent disjunctive structures. Notably, BSESN-KSE is conditionally dependent on the Chinese stock market, with no evidence of a lower tail. When combined with the CSI 300-BSESN, the first tree exhibits a moderate level of dependence (Kendall' $\tau = 0.25$). While the direct connection among the Indian and Pakistani stock markets is tenuous, they are both more closely linked to the Chinese market, with Chinese market fluctuations directly affecting these two markets. For the remainder, there is no tail correlation between market portfolios, either due to low dependence (low Kendall' τ coefficient) or an absence of tail correlation, which we will ignore.

Due to the fact that the current COVID crisis has significantly altered the business cycle, it is critical to examine the systemic and interplay effects of financial market return connectedness. To conduct further analysis of the COVID-19 pandemic's impact on the return spillover caused by market-wide connectedness. The TVP-VAR Connectedness approach enabled us to analyze net shock transmitters or receivers within asset systems, expanding our limited insight into the nature and scope of return shock propagation in the aftermath of the catastrophic COVID-19 outbreak.

According to Table 8, there is evidence of boosted correlation among financial assets following the global COVID-19 pandemic's onset, with TCI values (32.32%) indicating increased financial asset interconnectedness following the COVID-19 outbreak. With values of 48.20% and 42.04%, respectively, the Indian stock market and MSCI were the highest shock transmitters, while gold was the lowest giver (20.87%). Additionally, the BTC Index, China's stock market, and Pakistan's stock market all exceeded 20% in value. Interestingly, in the "FROM" column, Gold suffered the least damage (20.12%) from other markets, while the BSESN Index suffered the most (40.60%) from other markets. More importantly, we wanted to determine whether each asset received or transmitted more shocks, as indicated

by net spillover. Only MSCI and the Indian stock market were clearly net shock transmitters (6.86% and 7.60%, respectively), implying that they transmitted more shocks than they received. Besides, as evidenced by the negative value of their net spillover, the CSI index appears to have been the most adversely affected. The same is true for BTC and Pakistan, all of which have negative net premiums. As a result, investors in these markets are considering alternative assets. In the case of gold, we find an increase in the spread of spillovers from other asset classes to the gold market when compared to the overall sample (-2.36% to 0.75%). Just as gold has been shown to generate positive returns during economic downturns (e.g., Baur & Lucey, 2010; Klein *et al.*, 2018), we believe gold can be applied as a hedge and safe haven by global investors during the uncertainty period.

We then consider paired measures of directional connectedness, i.e., spillover effects between paired financial variables. We again use network diagrams to recognize the direction and intensity of net return spillovers in our selected paired markets during COVID-19, as shown in Figure 6. First, the network structure of return spillovers in the system after the COVID-19 outbreak is reported in Figure 6 as having changed significantly compared to the full sample period. Specifically, we find that MSCI has the highest correlation with the Bitcoin market during COVID-19, compared to MSCI's lower risk of spillover to the gold market following the COVID-19 outbreak. This result echoes the findings of Shahzad *et al.* (2020), who observe that gold provides higher and more stable returns to developed markets than Bitcoin when markets are in a bearish condition. At the same time, combining Figure 6 and Table 8, gold is not as strongly connected to risk as the Chinese and Indian stock markets, and we can confirm that gold can provide higher and more stable returns to the Indian and Chinese markets during COVID-19. In contrast, Bitcoin only sends spillovers to the Chinese and Pakistani markets. In addition, we report that the Indian stock market sends spillovers to the rest of the markets and that the Indian stock market has a strong impact on both the Chinese and Pakistan stock markets. In contrast, the Chinese and Pakistani stock markets are affected by spillovers from all markets. This is due to the outbreak of COVID-19, which first had a significant effect on the Chinese market, which dropped by around 15% in the first quarter of 2020 (KPMG, 2020). In contrast, the Pakistan stock market is more vulnerable to other stock markets during periods of market stress due to foreign direct investment and bilateral trade (Donaubauer *et al.*, 2020).

Our analysis contributes to these fields of study by providing preliminary econometrics evidence on the impacts of the COVID-19 outbreak on the dynamics of return spillovers across assets. Notable is the fact that, in terms of linkage, the connectedness between Bitcoin and other financial assets increased significantly following the COVID-19 outbreak, to the point where it became a net sender of spillover to the system. The COVID-19 outbreak also increased connectedness between regional and developed markets. The findings of this paper can assist investors in developing diversified cryptocurrency portfolios that maximize returns while balancing risk.

Robustness test

We set the forecast horizon to 150 days to test the robustness of our return connectedness findings in full sample analysis, and to determine if the trend of the dynamic connectedness index remains consistent. Figure 7 depicts the dynamic total connectedness index over a 150-day forecast horizon based on the TVP-VAR framework. Observably, the dynamics, frequency, and intensity of the connectedness index in Sections 4 are nearly identical. Consequently, the optional forecast horizon has no significant effect on the findings, and our results are compatible with the accuracy of our empirical conclusions.

Discussion

The Vine-Copula outcomes represent that extreme tail dependence exists in both the full sample period and the COVID-19 period, with the MSCI index having the strongest dependence on the Chinese and Indian markets in the total sample period; while during COVID-19, the Chinese market becomes the center of the dependence structure and there is extreme upper or lower tail dependence between many market pairs. We also construct a spillover network based on the TVP-VAR connectedness method to identify the intensity and direction of contagion of return spillover across time. We report that the MSCI index acts as the main spillover transmitter in both the full sample period and the COVID-19 period, while the Chinese and Pakistani markets mainly act as spillover receivers. At the same time, we obtain evidence that gold acts as a 'safe haven' against uncertainty shocks. This find-

ing is in accordance with Elsayed *et al.* (2022). These results provide useful information for investors with different levels of risk aversion and different investment strategies. For example, identifying the correlation structure of different markets as well as tail correlations can help investors build effective portfolios. In addition, these results are of importance to policymakers seeking to pursue policies during periods of market stress (e.g., COVID-19) and to track the risk transmission network across the spillover system. In particular, changes in the structure of interdependence and the correlation of risk spillovers in the system over time may help policymakers develop differentiated and flexible regulations in times of crisis.

The following empirical results are noteworthy: As shown in Figure 5, we find that the MSCI Developed Markets Index acts as a consistent net volatility spillover pass-through to all markets over the full sample period, implying that major South Asian markets, Chinese markets, and gold and Bitcoin markets are subject to information and risk spillovers from the MSCI index, a finding consistent with Mensi *et al.* (2021). This is because as international investors become more involved in these markets, their vulnerabilities become more susceptible to global market dynamics. The Chinese market is most significantly affected by the MSCI spillover over the full sample period, while there is only a net spillover from the Chinese market to the Pakistani stock market. This shows that the Chinese market is more exposed to risks from international markets. According to Figure 5, the Pakistani market is subject to spillovers from all other markets over the full sample period. Next, we find that there is a net spillover from the Indian market to the Chinese and Pakistani markets over the sample period. Combined with Table 6, we find that the Indian market has a 12.44% spillover effect on the MSCI index, while the MSCI Developed Markets Index has a 14.50% spillover effect on the Indian market. This finding reflects the fact that due to the internationalization of the Indian market and the high share of foreign trading, any significant change in the global market will quickly affect the Indian market and vice versa. In contrast, the Chinese market is less open to the outside world than the Indian market, as evidenced by the strict foreign investment regime. This explains why the return of the Chinese market send to the MSCI Developed Markets Index only by 5.69%, which is lower than that of the Indian market. Finally, China is an important market for Bitcoin and gold, despite the fact that the Chinese government currently bans cryptocurrency trading (Cheng & Yen, 2020). However, according to Figure 5, gold return does not seem to spill over signifi-

cantly into the Chinese market but combined with the findings of Corbet *et al.* (2020) and Shahzad *et al.* (2019), over the whole sample period, we infer that gold is not a major hedge against Chinese market volatility. Bitcoin, on either hand, may be viewed as a diverse asset for the Chinese stock market (Kliber *et al.*, 2019).

Based on the reports in Table 7, we can draw the following conclusions: (i) Following the COVID-19 outbreak, China's stock market became a focal point for volatility spillover. This is demonstrated by the fact that the majority of markets and market portfolios in the first and second trees are dependent on the Chinese market or are conditionally dependent on it; (ii) the Vine-Copula structure's tail correlation coefficients indicate that the majority of markets either lack tail correlation following the COVID-19 outbreak, or exhibit extreme tail correlation, such as only upper or lower tails.

Based on the results shown in Table 8, we can further analyze the results of the directional return spillover index in conjunction with the spillover values in order to obtain information that cannot be observed in Figure 6. We note that the analyzed values of paired directional connectedness are significantly larger than those found in the overall sample of Table 6. So, this connectedness index is highly unstable. We can say that the current COVID-19 crisis is causing structural changes in financial market connectedness. Indeed, as shown in Table 8, while spillovers between Indian stock markets and developed markets remain large, the spillover effect from Indian markets to developed markets (16.47%) is larger than that from developed markets to Indian markets (14.80%). This offers evidence that the spillover effect from the Indian to the MSCI was more significant during COVID-19 relative to the full sample period. Using the similar reasoning, we can also highlight that the MSCI spillover effect to the Pakistan and China markets was more significant during COVID-19. Meanwhile, the spillover effect of Bitcoin on MSCI markets was high during COVID-19, reaching over 4%. This is because Bitcoin's speculative nature and impact on mainstream assets made it a stress transmitter after the COVID-19 outbreak, a situation that was particularly evident in developed markets. Particularly intriguing is the increase in two-way return spillovers between the Indian and Pakistani markets following the COVID-19 outbreak (13.16% and 15.77% respectively), and what should not be overlooked is the increase in connectedness during turbulent times. During the financial crisis,

there is evidence of significant return spillovers in the risk patterns of South Asian markets (Iqbal *et al.*, 2020).

Conclusions

Gold is a hard currency asset used for international liquidity settlement and a critical asset for value preservation, whereas Bitcoin is a popular alternative asset and the most prominent cryptocurrency underlying at the moment. The aim of this research is to provide econometrics evidence of dependence structures and return spillovers from gold and Bitcoin to major China-South Asia stock markets in the context of risk shocks to global stock markets. The findings are relevant to understanding South Asia's regional economic structure. And, in contrast to previous research, the findings of this paper contribute to the analysis of China's linkages with major South Asian economies (India and Pakistan) during times of global shocks (especially COVID-19), as well as to the further investigation of gold and Bitcoin's dependence and volatility connectedness on the aforementioned markets.

We use a combination of different econometrics methods, including the GARCH-Vine-Copula and TVP-VAR Connectedness approach to examine the tail-dependence framework and network of return spillovers between major South Asian markets, Chinese and developed markets, as well as gold and Bitcoin. The following are the findings of our empirical research: (a) The dependence structure of paired markets is an R-Vine structure; (b) many market portfolios have an extreme tail dependence structure, which means that only the upper or lower tails are correlated; and (c) The TVP-VAR Connectedness study results confirm the increasing connectedness across financial systems during the COVID-19 outbreak. Throughout the sample period and the COVID-19 period, MSCI was the only net return transmitter. In contrast to gold, which became a net transmitter of volatility during the COVID-19 outbreak, Bitcoin became a net receiver of return throughout the COVID-19 era. The findings of this paper suggest that gold and Bitcoin are highly externally correlated in paired markets as hedging and safe-haven assets. This can benefit policymakers in the countries concerned, particularly in the context of global shocks, and can assist investors in allocating assets based on their risk tolerance. Meanwhile, the Chinese stock market is less internationalized than the Indian stock market because

it is not as well connected to global markets as the Indian stock market. As a new asset class, Bitcoin has significant implications for asset diversification.

Specifically, policymakers in the three countries should develop practical strategies to prevent shocks from developed markets, so that financial authorities in the three countries can respond quickly to global financial risks and make reasonable and appropriate policy adjustments. At the same time, policymakers should be concerned about the high speculative risks and the presence of illegal operations such as money laundering in the Bitcoin market and strengthen regulation of the Bitcoin market.

This research also has some limitations, such as the limited number of markets examined and the fact that another novel methodology could be applied depending on data availability. Further analysis of other asset classes, such as the inclusion of crude oil markets, could be undertaken in the future when examining the relationship between regional equity markets and other emerging financial markets. The use updated forecasting methods such as novel quantile-based return frequency spillover measures to simultaneously examine tail risk, the structure of connectedness in the time and frequency domains may be preferred.

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Annex

Table 1. Basic analysis of return data for all markets

	BTC	MSCI	CSI	KSE	BSESN	Gold
Mean	0.4684	0.0465	0.0373	0.0243	0.0561	0.0355
Mini	-31.9439	-10.4412	-8.2087	-7.8632	-11.4702	-5.1069
Max	23.7246	6.4392	7.4263	6.9267	8.5947	11.2197
Std.Dev	5.0549	1.0703	1.4066	1.2473	1.2288	1.0382
Skew	-0.4120	-1.6379	-0.6460	-0.6046	-0.9704	0.8370
Kurtosis	4.8043	20.5399	4.9147	5.6255	15.5427	14.4481
Jarque-Bera	1174.6***	21353.0***	1276.4***	1636.1***	12111.0***	10444.0***
ARCH-LM(20)	63.85***	607.12***	101.84***	188.61***	396.49***	69.46***
ADF	-9.52***	-9.99***	-10.39***	-9.88***	-10.05***	-9.36***
Q(20)	30.11*	203.36***	125.929***	42.94***	74.98***	38.73***

Note: The table demonstrates summary statistics of daily returns from 14 September 2015 to 30 March 2021. Jarque-Bera statistic is a test of normality. Q(20) is the Ljung-Box test of serial correlation of up to 20 lags in the statistics of the return for serial correlation of order 20 in returns. ARCH-LM is the LM test for autoregressive conditional heteroscedasticity. ***, ** and * indicate significant levels at 1%, 5% and 10%, respectively. BTC indicates the Bitcoin market; MSCI indicates the MSCI Global Market Index; CSI indicates the Chinese CSI 300 index; KSE indicates the Karachi Stock Exchange of Pakistan; BSESN indicates the Indian BSE Sensex index.

Table 2. Estimation of the marginal distribution

	BTC	MSCI	CSI	KSE	BSESN	Gold
C_0	0.3868***	0.0534***	0.0711**	0.0414	0.0480**	0.0252
C_1	0.0213	0.0688**	-0.0017	0.1624***	0.0647**	-0.0448*
ω	0.2761	0.0181***	0.0215**	0.0647***	0.0349***	0.0070**
α	0.1306**	0.0030	0.0634***	0.0066	0.0000	0.0265**
β	0.8908**	0.8645***	0.9156***	0.8537***	0.8811***	0.9734**
γ	-0.0442	0.2225***	0.0284	0.1966***	0.1732***	-0.0123
ν	3.3167***	4.2910**	4.4126***	5.0873***	5.6743***	3.5461**
λ	1.0223***	0.8764**	0.9854***	0.9658***	0.8970***	0.9715**
LL	-3358.029	-1256.768	-1871.099	-1729.929	-1564.980	-1523.812
AIC	5.705	2.144	3.185	2.946	2.666	2.596
BIC	5.740	2.178	3.219	2.980	2.701	2.631
K-S	0.0338 (0.1358)	0.0233 (0.5444)	0.0160 (0.9237)	0.0188 (0.7986)	0.0203 (0.7186)	0.0140 (0.9746)

Note: This table provides parameter estimates of marginal distribution models in parentheses, the meaning of parameter as Eq.(1). K-S defines the Kolmogorov-Smirnov bootstrapping test. ***, ** and * indicate confidence levels at 1%, 5% and 10%, respectively.

Table 3. Goodness-of-fit tests for different Vine-Copula models

	R-Vine	C-Vine	D-Vine
AIC	-446.96*	-444.73	-444.22
BIC	-320.13	-322.97	-327.54*
MLE	248.48*	246.37	245.11

Note: This table shows the information criteria for the three Vines. The best copula fit is selected based on the minimum Akaike information criterion (AIC) and Bayesian information criterion (BIC) and the maximum likelihood estimation (MLE) value. * represents the chosen optimal Copula function.

Table 4. Vuong Test

	D-Value	P-Value
C-Vine V.S. D-Vine	0.2552927	0.798497
R-Vine V.S. C-Vine	0.4029747	0.6869668
R-Vine V.S. D-Vine	0.8588613	0.3904171

Note: This table reports the Vuong test with null that Three Vines are statistically equivalent. The results indicate that we cannot reject the null hypothesis.

Table 5. Results of the vine-copula models for the six pair markets in the full sample period

Vine edge	Pair-Copula	Parameter 1	Parameter 2	Kendall' τ	Upper	Lower
2 5	<i>BB1</i>	0.31	1.15	0.25	0.17	0.15
3 2	<i>Survival BB1</i>	0.11	1.16	0.19	0.00	0.19
3 4	<i>Survival Gumbel</i>	1.11	0.00	0.10	-	0.14
6 1	<i>Joe</i>	1.06	0.00	0.03	0.08	-
6 3	<i>Student's-t</i>	0.06	7.39	0.04	0.02	0.02
3,5 2	<i>Student's-t</i>	0.20	10.58	0.13	0.02	0.02
4,2 3	<i>Student's-t</i>	0.04	11.59	0.03	0.00	0.00
6,4 3	<i>Student's-t</i>	0.01	11.16	0.01	0.00	0.00
3,1 6	<i>Student's-t</i>	0.03	8.05	0.02	0.02	0.02
4,5 3,2	<i>Clayton</i>	0.07	0.00	0.03	-	0.00
6,2 4,3	<i>Student's-t</i>	0.00	7.94	0.00	0.02	0.02
1,4 6,3	<i>Rotated Joe 270 degrees</i>	-1.07	0.00	-0.04	-	-
6,5 1,3,2	<i>Student's-t</i>	-0.02	13.16	-0.01	0.00	0.00
1,2 6,4,3	<i>Rotated Tawn type 1 180 degrees</i>	1.92	0.01	0.01	-	0.01
1,5 6,4,3,2	<i>Joe</i>	1.04	0.00	0.02	0.05	-
Type: R-vine	Log likelihood: 248.48		AIC: -446.96		BIC: -320.13	

Note: The numbers 1, 2, 3, 4, 5, 6 represent BTC, MSCI, CSI 300, KSE, BSESN, Gold. The types of copula functions are presented in the second column, showed 'Pair-Copula'. Parameters 1 and 2 are two parameters applied to define the pair-copula. Upper and Lower show tail dependence. Kendall' τ measures the similarity of the orderings of the data; the larger the value of τ for the Kendall rank dependence coefficient, the more significant the dependence among the paired markets.

Table 6. Dynamic connectedness table

	BTC	MSCI	CSI	KSE	BSESN	Gold	FROM
BTC	87.70	3.94	1.43	1.56	2.16	3.22	12.30
MSCI	3.27	72.71	5.69	2.57	12.44	3.33	27.29
CSI	3.66	10.41	74.60	3.26	5.73	2.34	25.40
KSE	3.47	4.33	3.88	80.76	4.97	2.59	19.24
BSESN	2.66	14.50	5.23	4.52	70.63	2.46	29.37
Gold	3.29	4.87	2.32	2.56	3.24	83.17	16.29
TO others	16.35	38.05	18.54	14.47	28.55	13.93	129.89
NET	4.05	10.77	-6.86	-4.77	-0.83	-2.36	TCI=21.65%
NPDC	1.00	0.00	4.00	5.00	2.00	3.00	

Notes: The TCI is the total connectedness index of the system of all markets. The forecast horizon is 100 days.

Table 7. Results of the vine-copula models in the COVID-19 period

Vine edge	Pair-Copula	Parameter 1	Parameter 2	Kendall' τ	Upper	Lower
3 4	<i>Survival Gumbel</i>	1.29	0.00	0.23	-	0.29
3 1	<i>Survival BB8</i>	1.59	0.89	0.16	-	-
5 2	<i>BB1</i>	0.33	1.28	0.33	0.28	0.20
3 5	<i>Student's-t</i>	0.28	4.79	0.25	0.16	0.16
6 3	<i>Independence</i>	0.22	0.00	0.14	-	-
5,4 3	<i>Clayton</i>	0.23	0.00	0.10	-	0.05
5,1 3	<i>Gumbel</i>	1.09	0.00	0.08	0.11	-
3,2 5	<i>Frank</i>	1.37	0.00	0.15	-	-
6,5 3	<i>Independence</i>	-	-	0.00	-	-
1,4 5,3	<i>Tawn type 1</i>	1.51	0.13	0.08	0.10	-
2,1 5,3	<i>Independence</i>	-	-	0.00	-	-
6,2 3,5	<i>Student's-t</i>	0.07	7.05	0.05	0.03	0.03
2,4 1,5,3	<i>Independence</i>	-	-	0.00	-	-
6,1 2,5,3	<i>Rotated Tawn type 1 180 degrees</i>	3.41	0.05	0.05	-	0.05
6,4 2,1,5,3	<i>Independence</i>	3.41	0.05	0.05	-	0.05
Type: R-vine	Log likelihood: 111.3		AIC: -188.61		BIC: -128.34	

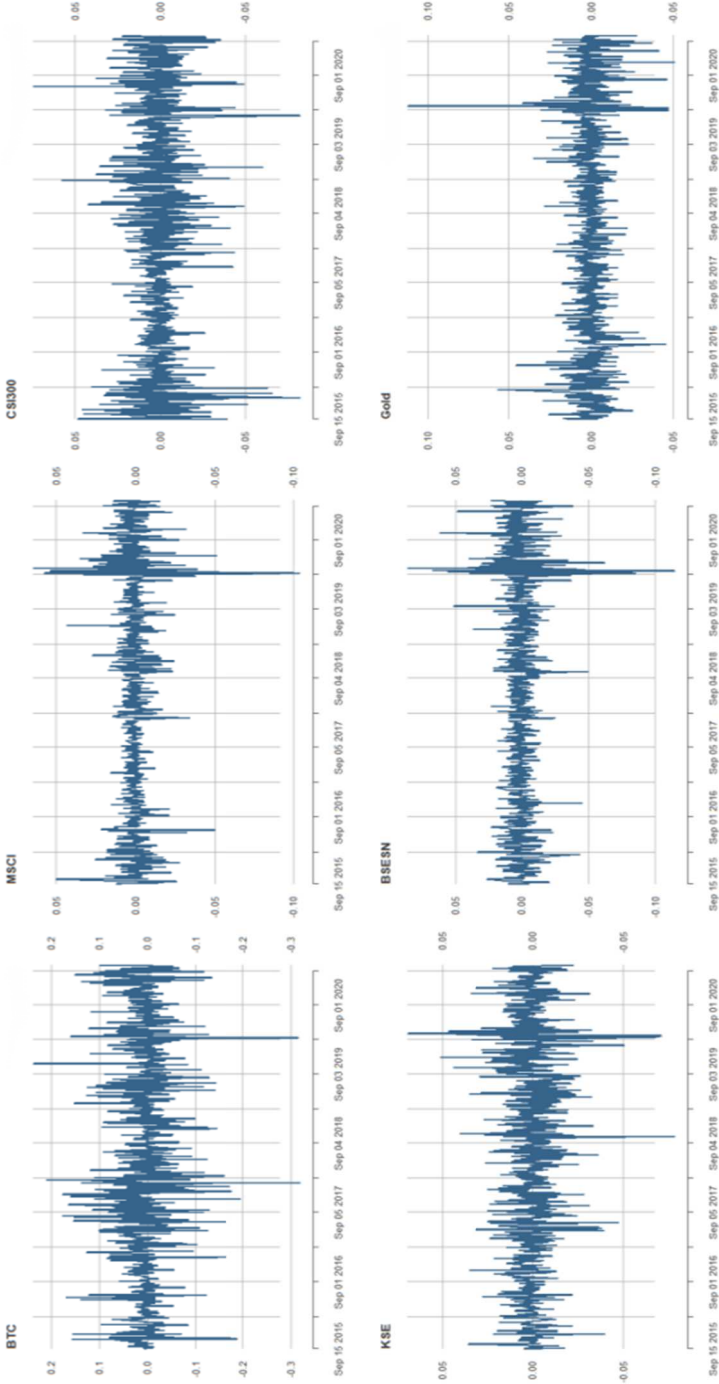
Note: The numbers 1, 2, 3, 4, 5, 6 represent BTC, MSCI, CSI 300, KSE, BSESN, Gold. The family of copula models selected for the nine paired markets are showed in the second column, showed 'Pair-Copula'. Parameters 1 and 2 are two parameters applied to determine the pair-copula model. Upper and Lower indicate tail dependence. Kendall' τ measures the similarity of the orderings of the data; the larger the value of τ for the Kendall rank dependence coefficient, the more significant the dependence between the paired markets.

Table 8. Dynamic Connectedness in COVID-19 Period

	BTC	MSCI	CSI	KSE	BSESN	Gold	FROM
BTC	75.07	8.45	3.70	3.37	3.75	5.65	24.93
MSCI	4.18	64.83	6.80	3.43	16.47	4.30	35.17
CSI	5.16	7.33	64.35	9.22	9.53	4.41	35.65
KSE	3.76	5.07	9.00	62.56	15.77	3.84	37.44
BSESN	3.24	14.80	6.72	13.16	59.40	2.68	40.60
Gold	4.86	6.38	3.67	2.54	2.66	79.88	20.12
TO others	21.20	42.04	29.88	31.72	48.20	20.87	193.91
NET	-3.73	6.86	-5.77	-5.72	7.60	0.75	<i>TCI=32.32 %</i>
NPDC	3.00	1.00	5.00	4.00	1.00	1.00	

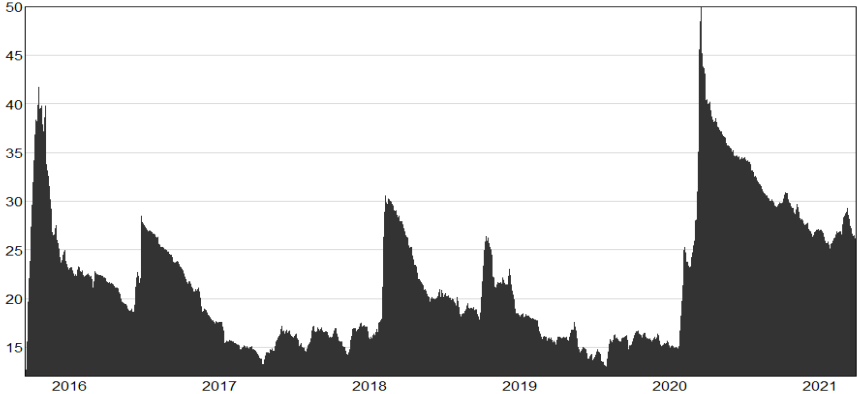
Notes: The TCI is the total connectedness index of the system of all markets. The forecast horizon is 100 days.

Figure 1. A plot of daily returns of paired markets



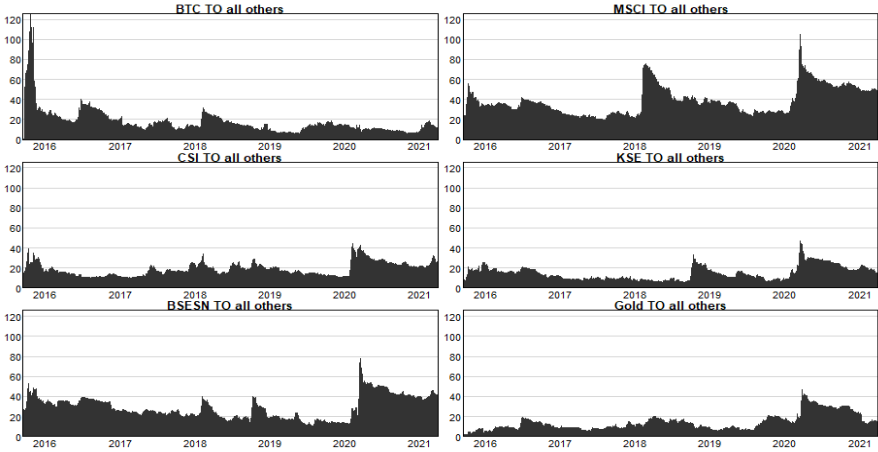
Source: calculations based on RStudio.

Figure 2. Dynamic total connectedness (The forecast horizon is 100 days)



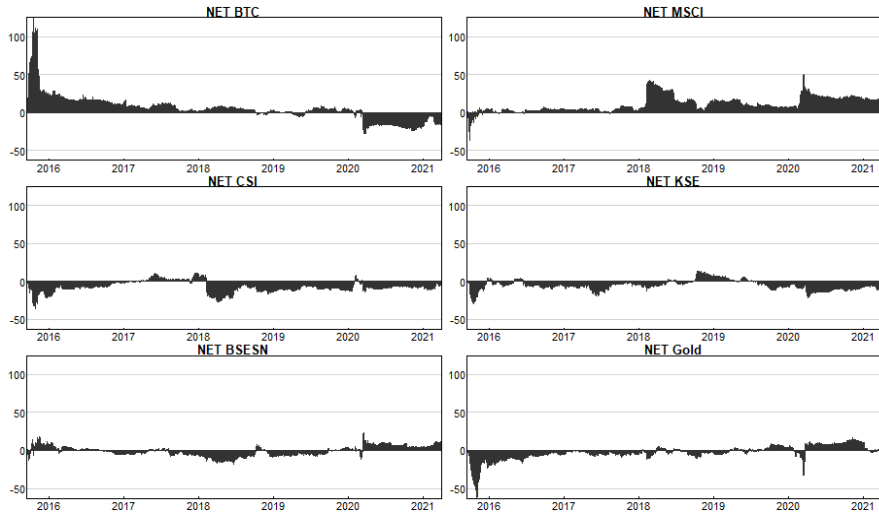
Source: calculations based on R Studio.

Figure 3. Total directional connectedness to others



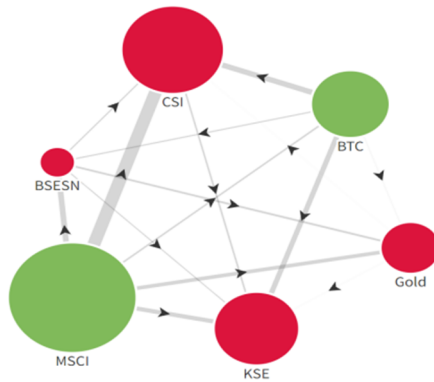
Source: calculations based on R Studio.

Figure 4. Net total directional connectedness



Source: calculations based on R Studio.

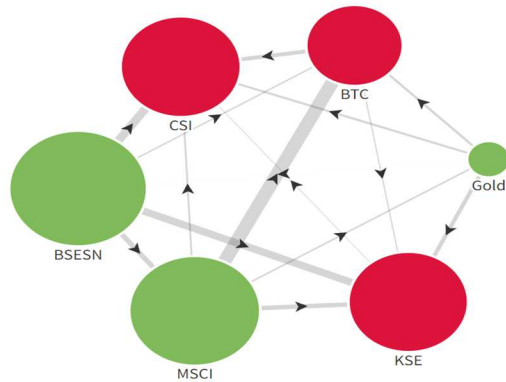
Figure 5. Net pairwise direction network plot of full sample period



Note: The graph shows the net spillover in pairs of directions between all markets in the TVP-VAR Connectedness model. The colour of the nodes defines whether the market is a net transmitter/receiver of return spillover. A larger (smaller) node indicates that it is a larger (smaller) source of spillovers in the system. Green indicates a return spillover transmitter, while red indicates a network receiver. In addition, the thickness of the line connecting the two nodes and the direction of the arrow show the intensity and direction of return spillover among each pair of markets. The thicker the line, the stronger the return spillover.

Source: calculations based on R Studio.

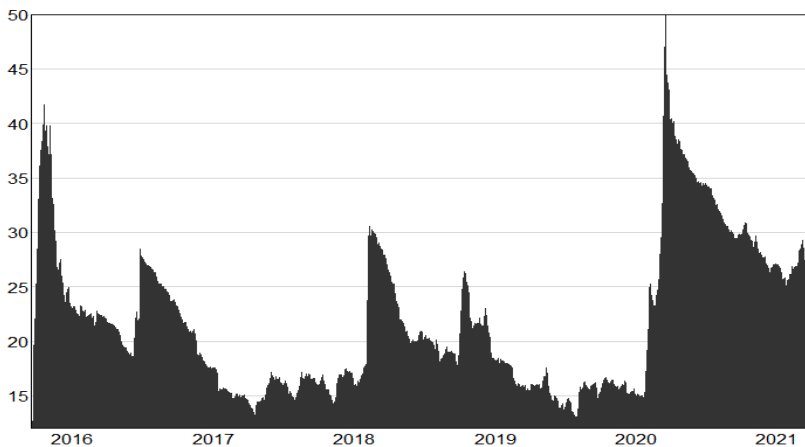
Figure 6. Net pairwise direction network plot during COVID-19



Note: The graph presents the net spillover in pairs of directions between all markets in the TVP-VAR Connectedness model. The colour of the nodes indicates whether the market is a net transmitter/receiver of return spillover. A larger (smaller) node indicates that it is a larger (smaller) source of spillovers in the system. Green indicates a return spillover transmitter, while red indicates a network receiver. In addition, the thickness of the line connecting the two nodes and the direction of the arrow show the intensity and direction of return spillover among each pair of markets. The thicker the line, the stronger the return spillover.

Source: calculations based on R Studio.

Figure 7. Dynamic total connectedness (The forecast horizon is 150 days)



Source: calculations based on R Studio.