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# COVID-19 and stock returns: Evidence from the Markov switching dependence approach

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ABSTRACT

This paper aims to investigate the regime-switching and time-varying dependence between the COVID-19 pandemic and the US stock markets using a Markov-switching framework. It makes two contributions to the empirical literature by showing that: (a) the variations of the daily reported COVID-19 cases and cumulative COVID-19 deaths induced asymmetric lower (left) and upper (right) tail dependence with the stock markets, and its left and right tail dependence exhibited significant time-varying trends; and (b) the left and right tail dependence between the stock markets and the pandemic exhibited significant regime-switching behaviours, with its switching probabilities in the higher tail dependence stage all being greater than in the lower tail dependence stage after 1 December 2019. Moreover, given that there is concurrent but significant financial market reaction to any unexpected emergence of a transmittable respirational disease or a natural calamity, the outcomes have some vital implications to market players and policymakers.

## 1. Introduction

The COVID-19 pandemic emerged as a severe global health emergency in late-2019/early 2020 (BBC News, 27 July 2020), and went on to sweep across the entire planet (Tan et al., 2022). By 30 September 2020, the World Health Organization (WHO) reported 34,321,965 infections and 1085,991. At the end of March 2022, these figures jumped substantially, to 482.3 million and 6.1 million, respectively (BBC News, 29 March 2022). The US, Spain, Russia, the UK, Italy, Brazil, France, German, Turkey, and Iran were the top-10 countries in terms of the confirmed cumulative total of COVID-19 cases. Among them, the US alone witnessed the highest number of cases, totalling 7224,066 by the end of September 2020, and 973,075 casualties by the end of March 2022 (Johns Hopkins University, National Public Health Agencies, as of 29 March 2022). The most stringent COVID-19 prevention and control measures, starting from 1 February 2020, led to massive corporate shutdowns and/or insufficiency in production and supply chain disruptions, including logistical system blocks. Altogether, the rapid spread of COVID-19 created uncertainties in the growth of global economies, with a projected decline from + 3.4 % to − 4.4 % between October 2019 and October 2020 (Jabeen et al., 2022) and a decrease in global trade volumes of 21 % during March-April 2020 and 9.2 % overall in year 2020 (Barbero et al., 2021). Recurring negative media

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coverage worsened investor expectation and sentiment (Papakyriakou et al., 2019), causing shocks, adverse moods and panic-selling due to fears of profit losses, resulting eventually in stock price fluctuations as well as market volatility and sporadic crashes (Sun et al., 2016; Huang, 2018; Zhu et al., 2018; Fan et al., 2019). As of 24 February 2020, the pandemic-led uncertainties saw a loss of USD 6 trillion in global stock markets (Ozili and Arun, 2020) and volatility expectations (captured by the "fear index") resulted in a loss of USD 5 trillion in the S&P 500 index alone (Onali, 2020). In Italy, the Netherlands and Switzerland, the continued rise in the number of deaths severely impacted S&P 500 returns (Just and Echaust, 2020). In Germany, the UK and Japan, stock market trading volumes dropped by 30–40 % (Tan et al., 2022). Overall, the pandemic showed unprecedented influence on the global financial systems, institutions, foreign exchange and commodity market, and exposed the latter's fragile nature of response to unexpected calamities (Abedin et al., 2021; Ahmed et al., 2022, 2023; Ahmed and Sarkodie, 2021; Goodell and Goutte, 2021).

The COVID-19 pandemic provoked severe market shocks and strong regime-switching behaviours in global stock and energy markets, recording a downturn more substantial than the 2008 financial crisis (Yakubu and Sarkodie, 2021). The greatest example in this regard was the US stock markets, which witnessed greater market shocks and fluctuations than other markets. According to the S&P Global BMI (20 June 2018), the US hosts over one-half of global stock markets, indicating the vital role that the economic growth of the US plays in propelling the stock markets of all other countries. Alola et al. (2020) reported that daily deaths and economic uncertainty plunged the US into financial turmoil. According to the IMF World Economic Outlook (October 26, 2021), the US and China occupy the first two places in the top-10 lists of GDP and GDP per capita rankings (in nominal values). Although the gap between the US and China is falling in terms of nominal ranking, it still led China by $6 trillion in 2021, and was projected to continue holding the top position until 2050. These facts highlight the continued dominance of the US stock markets in the global financial system for another three decades, at least. The US stock markets showed significant interdependence with emerging and developed stock markets, financial market and commodity markets. The US stock markets have a particularly high tail dependence with China, Japan and Korea (Luo et al., 2011; Wang et al., 2011) and a stronger dependence with Asia and Europe than with China (Yang et al., 2018; Zhou et al., 2020).

In light of the above background, this paper corroborates the recommendations of Goodell (2020) and Yarovaya et al. (2020) and recognises the significance of making further investigations on the financial market dynamics due to its scope and scale of influence on the global financial systems, institutions, and commodity market (Goodell and Goutte, 2021). In this connection, this research therefore aims to explore how the outbreak of the COVID-19 pandemic crisis affected volatility in the US financial markets. In specific terms, given that the US stock markets may exhibit (a) lower and upper tail dependence with the COVID-19 pandemic in extreme circumstances, and (b) significant regime-switching behaviours in the pre- and post- pandemic periods, this paper aims to investigate the regime-switching and time-varying dependence between the pandemic and US stock markets (S&P500 and Dow Jones indices). In addressing the research aim, we follow the Markov switching technique to investigate the link between the evolution of the pandemic (growth rate of daily reported cases and growth rate of daily reported deaths) and daily data form the log-returns of the Dow Jones and the S&P500.

Methodologically, we examine the Symmetrized Joe-Clayton (SJC) copula to measure lower and upper tail dependence (Rajwani and Dilip, 2019). The uniqueness of using the copula function is that it offers information on both the degree and structure of dependence, something a simple linear correlation method is unable to provide (Reboredo, 2011). Moreover, given that US stock markets may exhibit significant regime-switching behaviours before and after the pandemic, we use the Markov regime-switching model (MRS) as a proxy for the regime-switching behaviours among basis and spike states, and dynamic copula models to proxy for the joint distribution and time-varying dependence structure among multi-variables. As the MRS model was developed of marginal distribution without switching structures and copula with switching parameters (Filho et al., 2012; Chang, 2017; Kumar et al., 2019; Ji et al., 2020), we seek to describe the regime-switching dependence structure during the COVID-19 pandemic and the returns of the S&P500 and Dow Jones indices as pre- and post-pandemic events. In sum, the Markov-switching SJC copula allows the parameters that govern the lower and upper tail dependence characteristics to switch between two different states. We are cautious that financial market returns are characterized by excess kurtosis and heavy tails, autocorrelation and volatility clustering, and accordingly model the density dependence function conditionally, indicating that the implied rank dependence and tail dependence are dynamic. In order to estimate the density distribution function, we use the Autoregressive Moving Average (ARMA) model and the Threshold Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model with a skewed t distribution. As Ghani and Rahim (2019) emphasized, GARCH is applied in a large and growing body of literature to allow accurate modelling and forecasting of volatility using financial data. This paper, however, applies the GJR-GARCH model, which is a simple extension of the GARCH model that uses an additional term to account for possible asymmetries (Youssef and Rowe, 2021, p. 57). This makes it a superior predictor of international stock return volatility than both GARCH and EGARCH (Donaldson and Kamstra, 2005). To the best of our knowledge, no study has been done to capture the regime-switching and time-varying dependence between the COVID-19 pandemic event and the US stock markets incorporating a combination of the GJR-GARCH model, the MRS model and the SJC copula function into the MRS time-varying SJC copula function.

In addition to the methodological contribution of this study, we claim to have made two main contributions to the empirical literature in comparison with contemporary findings (see Section 2. Literature Review) on stock market volatility and uncertainties associated with COVID-19. First, the variations of daily COVID-19 confirmed cases and cumulative death cases induced asymmetric lower (left) and upper (right) tail dependence with US stock markets, and its left and right tail dependence exhibit significant time-varying trends. Second, the left and right tail dependence between the US stock markets and the pandemic exhibited significant regime-switching behaviours, and the switching probabilities in the higher tail dependence stage were all greater than that in the lower tail dependence stage after 1 December 2019.

The remainder of the paper is arranged in the following order. Section 2 makes a review of literature on the regime-switching and time-varying dependence structure. Section 3 discusses our methodology and introduces the Markov switching time-varying dependence between US stock markets and the COVID-19 pandemic. Section 4 presents our data and descriptive statistics. Section 5 presents the major findings of the research and Section 6 draws some conclusions.

## 2. Literature review

In the wake of the fast-proliferating COVID-19 pandemic, a considerable amount of research was conducted on its impact on global stock markets in a reasonably short span of time (e.g., Akhtaruzzaman et al., 2020; Albulescu, 2020; Baker et al., 2020; Będowska-Sójka and Echaust, 2020; Gormsen and Koijen, 2020; Liu et al., 2021; Onali, 2020; Rahman et al., 2022; Yilmazkuday, 2020). A number of these research works used the Markov switching model to investigate the impact of pandemic on stock market returns, volatility, correlations and liquidity. For instance, Just and Echaust (2020) used this model to study stock market turbulence associated with the [data on] new cases and deaths in twelve selective countries including the US, China and a number of European countries where COVID-19 spread rapidly and caused a large number of deaths. Likewise, Onali (2020) used the Markov-switching model to investigate the effects of reported deaths on stock markets returns in Italy, the US, Spain, China, Iran, France and the UK. The study revealed a negative impact of death reports on stock market returns in Italy and France, rising threefold by the end of February 2020, but no impact on US stock market returns as measured by the Dow Jones and S&P500 indices. Another group of researchers has quantified the effects of pandemic-related news on the degree of volatility of stock markets. For instance, Baker et al. (2020) made a textual analysis and emphasized that the pandemic had a greater impact on market volatility than other similar diseases - such as Ebola or SARS - had in the past. As a pioneering attempt at the industry level, Goodell and Huynh (2020) used an "event study methodology" to gauge the reactions of 49 US-based industries to the abrupt COVID-related media broadcasts and analyze the abnormal returns in the stock markets during the December 2019 – February 2020 period. Other studies, such as Dharani et al. (2022), Liu, Huynh and Dai (2021), Akhtaruzzaman et al. (2020), and Albulescu (2020) analyzed the effects of official declarations of cases and deaths on stock markets. Liu et al. (2021) scrutinized the "fear factor" to assess the possible nexus between the pandemic and the crash risk in Chinese stock markets and suggested that fear sentiment enhances the damaging influence of the pandemic on stock market and escalates crash risk. Albulescu (2020) found that new cases reported inside, and outside China had a positive effect on the Chicago Board Options Exchange's (CBOE) volatility index (VIX), commonly known as "fear index". Akhtaruzzaman et al. (2020) suggested that China and Japan experienced the "contagion effect" (transmission of spillovers during COVID-19) on stock markets in other countries (e.g., G7). This aligns well with Onali (2020), who observed volatility in the US stocks (Dow Jones and S&P500) as a result of the reported changes in the number of COVID-19 cases and deaths in countries outside the US. Also, Onali (2020) suggested a regime switch (from a low to a high volatility regime) in the nexus between volatility expectations and stock market returns by the end of February 2020. More recently, Huynh et al. (2021) applied a newly constructed index (called "feverish sentiment index") that comprised of six behavioural factors (media coverage, fake news, panic, sentiment, media hype and infodemic) and investigated the returns and volatility in the stock markets of the world's 17 largest economies. Using a time-varying parameter-vector auto-regression (TVP-VAR), the study found that investor sentiment positively (negatively) predicted market volatility (returns) between January 2020 and February 2021.

For an efficient stock market, all valuable information must be reflected accurately and in a timely manner in stock price trends (Aitsahlia and Yoon, 2016; Urquhart and Mcgroarty, 2016; Mills and Salaga, 2018). Accordingly, stock markets enjoy stability, but the problem of illiquidity arises when markets start showing volatility (Będowska-Sójka and Echaust, 2020). Stock markets in different countries exhibit significantly higher divergences in terms of their dependence structure. Emerging stock markets have a stronger long-range (or long memory) dependence in equity returns than those of developed economies (Cajueiro and Tabak, 2008; Dajcman, 2012; Gil-Alana et al., 2013; Ergen, 2014; Mokni and Mansouri, 2017). Crude oil spot and futures returns exhibit a time-varying and asymmetric dependence (Chang, 2012). The US, Taiwanese and Korean stock markets exhibit a degree of time-varying duration dependence and variations of asymmetry patterns (Chong et al., 2010; Kim et al., 2011; Frezza, 2012). Central and Eastern European (CEE) stock markets and selective Eurozone stock markets reveal a dynamic and extreme tail dependence structure (Dajcman, 2013; Castro-Camilo et al., 2018; Nitoi and Pochea, 2020). Stock markets in Asia, Europe and the US exhibit an asymmetric dependence and high contagion risks (Abbara and Zevallos, 2014; Shim et al., 2016; Bensaida et al., 2018; Luo and Chen, 2018). European and US stock markets show a structurally stable process of information transmission (Maderitsch, 2015). The US credit and stock markets have an asymmetric association, and their link depends on both the sign and size of the stock market shocks (Shahzad et al., 2018). Investor sentiment and stock returns in the European stock markets exhibit an extreme dependence structure (Horta and Lobao, 2017). Major stock indexes in America, Europe and Asia reveal an incline in the dependence structure to the increasing popularity of index products (Baltussen et al., 2019; Ji et al., 2019). The BRIC stock and foreign exchange markets exhibit a symmetric tail dependence structure (Kumar et al., 2019). Two recent economic and political crises had magnificent impact on the level of stock market dependence and volatility spillovers between Qatar and its GCC neighbours (Charfeddine and Refai, 2019). Economic policy uncertainty and global economic factors explain the asymmetric dependence structure with stock markets in Asia, America and Europe (Guo et al., 2018; Dong et al., 2020).

Currently, there are 60 major stock exchanges in the world, varying in size and trading volume. Statista Research Department (1 February 2022) reported that the New York Stock Exchange (NYSE) and the NASDAQ are the largest stock exchanges in the world, with an equity market capitalisation of $27.7 trillion and $26.6 trillion respectively, as of December 2021. The NYSE lists over 2400 companies, spanning sectors such as finance, health and energy, whereas the NASDAQ lists over 3500 companies, holding the world's largest market capitalisation of technology stocks. Both the NYSE and the NASDAQ together have a market capitalisation of $45 trillion, comprising about 45 % of the total held by the top-20 stock markets of the world. Following the NYSE and NASDAQ, the total market capitalisation of China's leading stock exchanges (i.e., Shanghai, Shenzhen and Hong Kong), the EU (Euronext), Japan (Tokyo), the UK (LSE Group) was valued at about $35.5 trillion, i.e., lesser than the US stock markets by $9.5 trillion, as of December 2021. Due to the obvious significance of the latter in global business and finance, we reviewed prominent studies of the US context and noted various degrees of time-varying duration dependence and variations in asymmetry patterns (Chong et al., 2010; Kim et al., 2011; Frezza, 2012). For example, the major stock indexes in the US reveal links of an incline in dependence structure to the increasing popularity of index products, and this aligns with Asian and European market behaviour (Baltussen et al., 2019; Ji et al., 2019). Moreover, the US stock markets show an asymmetric association/dependence, and the link depends on both the sign and size of the stock market shocks (Shahzad et al., 2018), influenced by various factors related to uncertain economic policy and unfavourable global events (Guo et al., 2018; Dong et al., 2020). The US stock markets also exhibit high contagion risks from Asian and European markets (Abbara and Zevallos, 2014; Shim et al., 2016; Bensaida et al., 2018; Luo and Chen, 2018), which aligns well with Akhtaruzzaman et al.'s (2020) and Onali's (2020) observations, as discussed above. It also corroborates the findings of Albulescu (2020), who suggested how the US stock prices were disrupted and logged their lowest level by the end of February 2020, following an 8 % drop in the Shanghai stock market on 3 February 2020 due to a nexus between pandemic death rates and the VIX. Likewise, Huynh et al. (2021) found strong connectedness among the 17 largest economies of the world and suggested that the US, China, the UK, France and Italy were the epicentres of the sentimental shocks that affected the stock markets of the other economies. However, unlike Asia, a structurally stable process of information transmission is observable in the US stock markets, a practice that looks somewhat similar to that in Europe (Maderitsch, 2015).

The review above indicates some degree of similarity between US stock markets with their Asian and European counterparts in time-varying duration dependence and variations of asymmetry patterns. However, due to the large volume of market capitalisation and their influence on global business and finance, we aim to develop a clear understanding of the regime-switching behaviours of the US stock markets and their time-varying dependence in the pre- and post- pandemic periods, using the Markov switching model as a framework.

## 3. Research methodology

In the wake of the COVID-19 pandemic, which caused a significant degree of uncertainty in global economic growth and fluctuations in stock and energy markets, the US stock markets exhibited significant regime-switching behaviours, both before and after the pandemic broke out. This paper seeks to describe the regime-switching dependence structure between the returns of the S&P500 and Dow Jones indices and before and after the breakout of the COVID-19 pandemic. The Markov model is used to proxy for regime-switching behaviours among basis and spike states, and dynamic copula models are used to proxy for the joint distribution and time-varying dependence structure among multi variables. Based on the recent literature (Filho et al., 2012; Chang, 2017; and Ji et al., 2020), the Markov regime-switching copula models are developed of marginal distribution without switching structures and copula with switching parameters. In this section, we present our methodological approach in three steps: (a) the time-varying copula function (3.1); (b) the Markov switching time-varying copula modelling specification (3.2); and (c) the Markov switching time-varying copula regression (3.3).

### 3.1. The time-varying copula function

The copula models are used to proxy for the multivariant joint distribution functions, whose marginal distributions are the same on interval $(0,1)^n$. Here, for the returns of the US stock market index $x_1$ and the change in confirmed COVID-19 deaths $x_2$, a copula is used to assess the bivariate joint distribution function $f_{12}(x_1, x_2)$ for the stochastic variables. Following Afuecheta et al. (2020), the bivariate joint density function $f(x_1, x_2)$ of COVID-19 and stock returns can be formulated through the following copula function:

$$f_{(x_1,x_2)=C(\mu_1,\mu_2)}\prod_{i=1}^{2} f_i(x_i) \tag{1}$$

Where, $\mu_1 = F_1(x_1)$, $\mu_2 = F_2(x_2)$, $f_{i(x_i)}$ denotes the probability density function for the marginal $x_i$, and $C(\mu_1, \mu_2)$ denotes the state-dependent copula density function. The copula density function can be expressed as follows:

$$C(\mu_1,\mu_2) = \frac{f\left(F_1^{-1}\mu_1 * F_2^{-1}\mu_2\right)}{\prod\limits_{i=1} f_i\left(F_i^{-1}(\mu_i)\right)} \tag{2}$$

As discussed, the COVID-19 pandemic event created greater shocks and fluctuations in the US stock markets. Using tail dependence copula models, we measure and identify the model that is able to reproduce empirical realities or stylized realities in financial markets, including stock markets. The tail dependence measures assess the probabilities of an extreme event occurring in the stock markets, and the COVID-19 pandemic as the most severe public health emergency in 100 years to hit the US. Moreover, the tail dependence is completely expressed by the dependence structure among stock markets and the COVID-19 pandemic, and the related copula is not impacted by marginal distribution variations. Many copula functions existing as proxies for the tail dependence structure between financial markets. The COVID-19 pandemic and US stock markets may exhibit lower and upper tail dependence in the extreme circumstance. The Gumbel copula measures only lower tail dependence, while the Clayton copula measures only upper tail dependence. The Symmetrized Joe-Clayton copula (SJC), also known as BB7, can measure both lower and upper tail dependence. The SJC copula can be written as:

$$C_{JC}(\mu_1,\mu_2,\tau^U,\tau^L) = 1-\left(1-\left\{\left[1-(1-\mu_1)^k\right]^{-\gamma}+\left[1-(1-\mu_1)^k\right]^{-\gamma}-1\right\}^{\frac{1}{\gamma}}\right)^{\frac{1}{k}} \tag{3}$$

Where, $=\frac{1}{\log_2(2-\tau^U)}, \gamma = -\frac{1}{\log_2(2-\tau^L)}$, and $\tau^U,\tau^L \in (0,1)$. The SJC copula has lower and upper tail dependence parameters,$\tau^U$,$\tau^L$ measuring the upper tail dependence and the lower tail dependence respectively, which range freely and are non-dependent with each other.

Financial market returns are generalized and characterized by excess kurtosis and heavy tails, autocorrelation and volatility clustering. Accordingly, the density dependence function is modelled conditionally, indicating an implied rank dependence, whereas tail dependence is dynamic. In this study, we select the Autoregressive Moving Average (ARMA) model and the Threshold Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model with a skewed t distribution to estimate the density distribution function. Following H. Jiet al. (2019); Q. Ji et al. (2019) and Liu et al. (2019), the ARMA (p,q)-GJR-GARCH(m,n) skewed t model is defined as:

$$\begin{aligned} x_{i,t} &= \varphi_0 + \sum_{j=1}^{p}\varphi_j x_{i,t-j} + \sum_{j=1}^{q}\varphi_j\varepsilon_{i,t-j} \\ \varepsilon_{i,t} &= \sigma_{i,t}\mu_{i,t}, \mu_{i,t} \sim i.i.d, t_{v,\lambda} \\ \sigma^2_{i,t} &= \omega_i + \sum_{j=1}^{m}\left(\alpha_j+\gamma_j I_{i,t-j}\right)\varepsilon^2_{i,t-j} + \sum_{j=1}^{n}\beta_j\sigma^2_{i,t-j} \end{aligned} \tag{4}$$

Where $t_{v,\lambda}$ is a skewed t distribution with a mean of 0 and a variance of 1, $i=1,2$ is the returns of US stock markets and variations in the COVID-19 pandemic, $t=1,2,\cdots\ldots,T$, $T$ is the sample time series, $\varphi_{i,1,}\cdots\cdots\varphi_{i,p}$ are the coefficient of state variables autoregression with lag p, $\varphi_{i,1,}\cdots\cdots\varphi_{i,q}$ the coefficients of the residual errors with lag q, $\omega_i$ is the constant term, and$\alpha_j$, $\beta_j$, $\gamma_j$ are the coefficient of the prior residual errors and prior conditional volatility components. In line with Lawrence et al. (1993), the following model introduces a multivariate indicator vector to permit the asymmetric effects of negative and positive volatility shocks.

$$I_{i,t-j} = \begin{pmatrix} 1, if\,\varepsilon_{i,t-j} < 0(badnews) \\ 0, otherwise(goodnews) \end{pmatrix}$$

The forecasted coefficient ($\gamma_j$) of the above equation captures the leverage effect that we state the impact of positive and negative volatility shocks. Compared to positive shocks, specifically, a positive value refers that the negative ones have a larger impact. In Eq. (4), with connecting to Lawrence et al. (1993), the volatility process, i.e., the positivity and stationarity conditions are satisfied when the parameters guarantee the following constraints: $\omega_i > 0$, $\alpha_j$, $\beta_j$ and $\gamma_j \geq 0$, and $\gamma_j + \frac{\alpha_j+\beta_j}{2} < 1$. According to the literature (Donaldson and Kamstra, 2005; Brownlees et al., 2012; Laurent et al., 2012), the threshold GJR-GARCH model generally performs better than the GARCH generalized specification. Thus, including a leverage effect leads to enhanced forecasting performance.

### 3.2. The Markov switching time-varying copula modelling specification

The COVID-19 pandemic, as the greatest public health emergency in modern times, may have provoked higher market shocks and regime-switching behaviours in global stock and energy markets. The Markov-switching SJC copula allows the parameters governing the lower and upper tail dependence characteristics to switch between two different states. The unobserved random state variable $S_{i,t}$ is included into the copula function to describe the regime-switching copula model, assuming $S_{i,t}$ follows the principle of the Markov regime-switching process with the transition probability. The joint density function of the filtered $x_{1t}$ and $x_{2t}$ on being in regime is given by:

$$f\left(x_{1t},x_{2t}|\varnothing_{i,t-1};S_t=s\right) = \mathtt{C}_{S_t}\left(\mu_{1t},\mu_{2t}|\theta^{S_t}\right)\times\prod_{n=1}^{2}f_n(x_n) \tag{5}$$

Where $s \in (0,1)$, while 1 refers to a higher tail dependence regime, 0 refers to a lower tail dependence regime, $\mathtt{C}_{S_t}$ refers to the regime-switching copula function, and $\varnothing_{i,t-1}$ refers to the information set at time t-1. In line with Zhang et al. (2014), Xi and Manon (2014) and Zhu et al. (2019), the change in regime follows a Markov chain, indicated by the following transition probability matrix:

$$P = \begin{pmatrix} p_0 & 1-p_0 \\ 1-p_1 & p_1 \end{pmatrix} \tag{6}$$

Where$p_0$,$p_1$ are the conditional probabilities of being in the lower tail dependence regime and in the higher tail dependence regime, respectively.

### 3.3. The Markov switching time-varying copula regression

We state the regression of the Markov switching time-varying copula, which follows three steps, by measuring: first the parameter coefficients of two state variables using ARMA (p, q)-GJR-GARCH(1,1) with a skewed t distribution; second, the parameter coefficients of bivariate copula functions using the maximum likelihood and matrix estimation methods; and third, the parameter coefficients of the Markov switching time-varying copula. Let us assume $(\phi_1, \phi_2)$ and $\theta$ denote the parameter of the margins and the copula respectively. The log-likelihood function is decomposed by the likelihood function of the marginal distribution and the maximum likelihood function of the copula. The parameters of the copula are evaluated in two stages, by proxying: (a) the margin parameter coefficients; and (b) the copula parameter coefficients conditional on the margins. Hence, the likelihood function is given as:

$$L_{x_1,x_2,}(\phi,\theta) = \sum_{n=1}^{2} L_n(\phi_n) + L_{\mathsf{C}}(\phi_1,\phi_2;\theta) \tag{7}$$

$$= \sum_{n=1}^{2}\sum_{t=1}^{T} \ln f_n\left(x_{n,t};\phi_n\right) + \sum_{t=1}^{T} \ln \mathsf{C}(\mu_{1,t},\mu_{2,t};\theta)$$

Where our first step is estimating $\phi_1 = \text{argmax} \sum_{i=1}^{n} \ln f_1(x_{1t}|\phi_1)$ and $\phi_2 = \text{argmax} \sum_{i=1}^{n} \ln f_2(x_{2t}|\phi_2)$. Joe (2005) and Patton (2006) simulations approve that the efficiency loss is generally small in practice. The residual errors are extracted and normalized from the ARMA (p,q)-GJR-GARCH(1,1) with a skewed t distribution. The normalized residual errors are included into density copula functions with the probability integral transformation. We select the SJC copula function to proxy the upper and lower tail dependence between the US stock markets and the COVID-19 pandemic event. The parameter coefficients of the Markov switching time-varying copula function are regressed by the likelihood method. The logarithmic likelihood function is written in the form of the following equation:

$$L_{x_1,x_2,}(\phi,\theta_{t-1}) = \sum_{n=1}^{2}\sum_{t=1}^{T} \ln f_n\left(x_{n,t}|\theta_{t-1},\phi_n\right) + \sum_{t=1}^{T} \ln \mathsf{C}(\mu_{1,t},\mu_{2,t}|\theta_{t-1};\theta_{M,S_t}) \tag{8}$$

Where $\theta_M$ denotes the parameter set in the Markov time-varying copula and $s_t$ denotes the state variable at time t. We note that the parameter $\theta_M$ is measured using the likelihood estimation method:$\phi_M = \text{argmax} \sum_{i=1}^{T} \ln \mathsf{C}(\mu_{1,t},\mu_{2,t}|\theta_M)$. Due to the fact that the regression of the Markov switching time-varying copula function is more complex, this study goes through two phases to assess its parameter coefficients. Phase 1 regresses the parameters of marginal density distribution and phase 2 regresses the parameters of the Markov switching copula function. Nelsen (1999) provides the maximum likelihood estimation as a tool to quantify the probabilities of the Markov switching function. The main phases are regressed as follows:

Phase 1: the unconditional expected value in the $i$th state is set as the initial value:

where,

$$\Pr(S_0 = 0|\Omega_0) = \frac{1-p_1}{2-p_0-p_1} \tag{9}$$

$$\Pr(S_0 = 1|\Omega_0) = \frac{1-p_0}{2-p_0-p_1} \tag{10}$$

Phase 2: the computed prediction probability is given by:

$$\Pr(S_t = j|\Omega_{t-1}) = \sum_{i=1}^{2} \Pr(S_{t-1} = i|\Omega_{t-1}) \times \Pr(S_t = j|S_{t-1} = i) \tag{11}$$

The basic equation for the probability density function of the Markov switching copula function is as follows:

$$\mathsf{C}_{M,S_t}(\mu_{1,t},\mu_{2,t}|\theta_M,S_t) = \sum_{i=1}^{2} \Pr(S_{t-1} = i|\Omega_{t-1}) \times \mathsf{C}(\mu_1,\mu_2|\Omega_{t-1},\theta_M,S_t = j) \tag{12}$$

Phase 3: the filtered probability $\Pr(S_t|\Omega_t)$ is given as follows:

$$\Pr(S_t = j|\Omega_t) = \Pr(S_t = j|\Omega_{t-1},\mu_1,\mu_2)$$

$$= \frac{\mathsf{C}_{M,S_t}\left(\mu_{1,t},\mu_{2,t}|\Omega_{t-1},\theta_M,S_t = j\right) \times \Pr(S_t = j|\Omega_{t-1})}{\sum_{i=1}^{2} \Pr(S_{t-1} = i|\Omega_{t-1}) \times \mathsf{C}_j(\mu_1,\mu_2|\Omega_{t-1},\theta_M,S_t = j)} \tag{13}$$

$$= \frac{\mathsf{C}_{M,S_t}(\mu_1,\mu_2|\Omega_{t-1},\theta_M,S_t = j) \times \Pr(S_t = j|\Omega_{t-1})}{\mathsf{C}_{M,S_t}\left(\mu_{1,t},\mu_{2,t}|\Omega_{t-1},\theta_M,S_t\right)}$$

Aiming to achieve the convergence accuracy standards, we continuously iterate the results of simulation and get the parameters of the Markov switching time-varying copula function, employing the maximum likelihood method when the predicted probability and filtered probability are not smooth. On the basis of the approach used by Kim and Nelson (1999), the probabilities $\Pr(S_t|\Omega_{t-1})$ and $\Pr(S_t|\Omega_{t-1})$ are also smoothed out and the smoothed probabilities are estimated, proxying for the measurement of the probabilities in the full sample period. The smoothed probability is measured by the following equation:

$$\Pr(S_t = i|\Omega_t) = \sum_{i=1}^{2} p_{i,j} \times \frac{\Pr(S_{t+1} = j|\Omega_t) \times \Pr(S_{t+1} = i|\Omega_t)}{\Pr(S_{t+1} = j|\Omega_t)} \tag{14}$$

Where $t = T-1, T-2, \cdots\ldots, 2, 1$. In line with the method proposed by Patton (2006), the parameter $\theta$ of the SJC copula is estimated using the following conversation function:

$$\left\{ \begin{array}{l} \tau^{U}_{t,S_i} = {}^{2}\left(\omega_{U,S_i} + \beta_{U,S_i}\tau^{U}_{t-1,S_i} + \alpha_{U,S_i}\sum_{j=1}^{10}\frac{\|\mu_{1,t-j} - \mu_{2,t-j}\|}{10}\right) \\ \tau^{L}_{t,S_i} = {}^{2}\left(\omega_{L,S_i} + \beta_{L,S_i}\tau^{L}_{t-1,S_i} + \alpha_{L,S_i}\sum_{j=1}^{10}\frac{\|\mu_{1,t-j} - \mu_{2,t-j}\|}{10}\right) \end{array} \right\} \tag{15}$$

Where ${}^{2} = \frac{1}{1+e^{-x}}$, the main goal is realized through the range $\tau^{U}_{t}, \tau^{L}_{t} \in (0,1)$and the parameters of the Markov switching time-varying copula are formulated as:

$$\mathbb{C}_{Mt}(\mu_{1,t}, \mu_{2,t}|\Omega_{t-1}, \tau^{U}_{t,S_t}, \tau^{L}_{t,S_t}) = \pi_{Lt} \times \mathbb{C}_t(\mu_{1,t}, \mu_{2,t}|\Omega_{t-1}, \tau^{U}_{t,S_L}, \tau^{L}_{t,S_L}) + \pi_{Ht} \times \mathbb{C}_t(\mu_{1,t}, \mu_{2,t}|\Omega_{t-1}, \tau^{U}_{t,S_H}, \tau^{L}_{t,S_H}) \tag{16}$$

Where $\pi_{Lt}$,$\pi_{Ht}$ refers to the probabilities of lower and higher tail dependence in time t respectively, and $S_{Lt}$,$S_{Ht}$ refers to the state variables in the lower and higher tail dependence stages. Following the definition of Gray (1996), we generate the following equation:

$$\pi_{L,t} = P(S_t = L|\Omega_{t-1}) = p_0\left[\frac{\mathbb{C}^{L}_{t-1}, \pi_{L,t-1}}{\mathbb{C}^{L}_{t-1}, \pi_{L,t-1} + \mathbb{C}^{H}_{t-1}, \pi_{H,t-1}}\right] + (1-p_1) \times \frac{\mathbb{C}^{H}_{t-1}, \pi_{H,t-1}}{\mathbb{C}^{L}_{t-1}, \pi_{L,t-1} + \mathbb{C}^{H}_{t-1}, \pi_{H,t-1}} \tag{17}$$

$$\pi_{H,t} = 1 - \pi_{L,t}$$

Where $\mathbb{C}^{L}_{t-1}$ and $\mathbb{C}^{H}_{t-1}$ denote the conditional probability density of lower and higher tail dependence in the SJC copula at time t-1, respectively.

## 4. Data and descriptive statistics

Our database consists of two daily US financial market indicators - the Dow Jones index and the S&P500 index - over the period 1 October 2019–12 May 2021. For all the indicators, we use closing prices at 00:00 GMT. All indicator time series were collected from Thomson Reuters. Data on COVID-19 were obtained from the WHO for the sample period. We can observe the dynamics of the total number of daily reported COVID-19 cases and deaths in the US and the scale of their growth in Figs. 1 and 2, respectively. To account for the possible regime switching time-varying dependence structure among the US stock markets during the pre- and post-COVID-19 pandemic event, we divided the sample period into two equipotent subperiods, before and after 19 January 2020 (i.e., the day the WHO disclosed the pandemic data). We measured the S&P500 and Dow Jones daily returns by $R_{it} = \ln(\frac{P_{it}}{P_{it-1}})$. $P_{it}$ is the closing price of index $i$ at time $t$, as noted $RSP_{SP,t}$ and $RDO_t$, and the variation of daily reported COVID-19 cases and deaths by $\Delta RCV_t = \ln(\frac{RCV_t}{RCV_{t-1}})$ and $\Delta DCV_t = \ln(\frac{DCV_t}{DCV_{t-1}})$, with $RCV_t$ and $DCV_t$ the reported cases and deaths at time $t$.

Figs. 1 and 2 represent the evolution of the number of daily reported COVID-19 cases and deaths between 19 January 2020 and 12 May 2020. The period from 19 January 2020–4 March 2020 marks the beginning of a notable increase in daily reported COVID-19

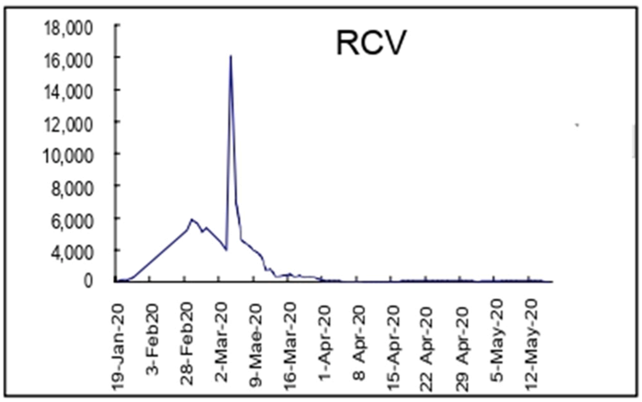


**Fig. 1.** Daily evolution of reported COVID-19 cases.

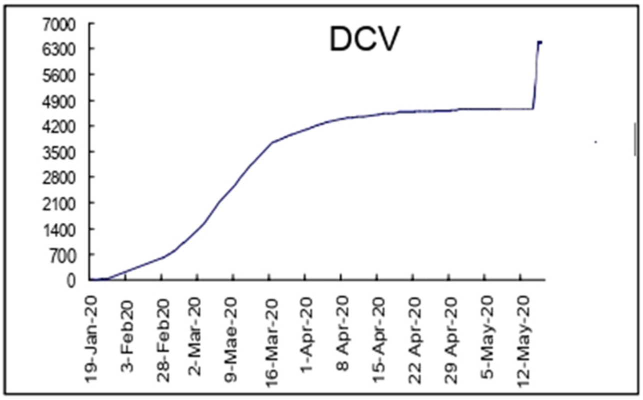


**Fig. 2.** Daily evolution of COVID-19 deaths.

cases. Then, daily reported cases appeared to decline until 11 May 2020. Daily COVID-19 deaths do not exhibit the same evolution, as they increased rapidly between 19 January 2020 and 17 April 2020, then fell until 12 May 2020.

The summary statistics in Table 1 show that the average returns of the S&P500 and Dow Jones stock market indices are − 0.21672 and − 0.21515, the standard deviations are 4.20252 and 4.20231, and their skewness coefficients are − 1.45905 and − 1.45872 respectively, and their kurtosis coefficients are 6.45932 and 6.45617, which confirm that for our study period the S&P500 and Dow Jones stock market present left skewness and steep kurtosis characteristics. The variations of daily reported COVID-19 cases and deaths have a mean of − 0.01928 and 0.1147 and a standard deviation of 0.80133 and 0.50349, respectively. Their coefficients for skewness are 1.28785 and 7.62658, and for kurtosis 7.89583 and 48.7211, respectively. The leptokurtic distribution with a right tail is confirmed for the variations of daily reported COVID-19 cases and deaths time series.

## 5. Empirical results

### *5.1. Time-varying movement between the S&P500 and Dow Jones stock markets and the COVID-19 pandemic*

The threshold GJR-GARCH model presents a good description of time-varying and leptokurtic characteristics (see Table 2).

Two main observations are observed in Table 2. First, the AIC and the BIC values are lower than − 500.0000, the values of the Levin and Lin test are all greater than 330.0000, and the time-varying movement between the US stock market and the COVID-19 pandemic mainly follows the GJR-GARCH model with a skewed t distribution. Second, the coefficients for the ARCH and GARCH terms are statistically significant at the 5 % and 1 % levels, respectively. The ARCH terms' coefficients for both the S&P500 and Dow Jones market returns are equal to 0.42306 and 0.36938, respectively, and this means that the squared residual errors indicate less significant impacts on actual conditional volatility at the 5 % level of statistical significance. The ARCH terms' coefficients for both daily variations of daily reported COVID-19 cases and deaths are equal to 0.86860 and 0.86042, respectively, suggesting that the prior squared residual errors show high significant impacts on actual conditional volatility at the 5 % level of statistical significance. The GJR term's coefficient (γ) is positive and significant for all variables, implying the absence of an asymmetric response of the selected variables to volatility shocks. If the asymmetry term, γ, is positive, then negative shocks increase return-volatility. Whether we sum the ARCH, GARCH, and GJR terms' coefficients, we find a result of 1, which meets and validates the GARCH model hypothesis. Overall, the findings imply that the variations of our selected variables have significant and persistent volatility clustering impacts.

### *5.2. Markov switching time-varying dependence between the S&P500 and Dow Jones markets and the COVID-19 pandemic*

Table 3 presents the results of the test for the Markov switching time-varying copula model, which analyses the regime-switching dynamic dependence between the COVID-19 pandemic event and the US stock markets. We find that all the maximum likelihood values are higher than 14.0000 and both AIC and SIC values are lower than − 29.0000, so the Markov switching time-varying copula

**Table 1**
Summary statistics.

| | RSP | RDO | ΔRCV | ΔDCV |
|---|---|---|---|---|
| Mean | -0.21672 | -0.21515 | -0.01928 | 0.01147 |
| Min | -12.8530 | -12.8448 | -1.72995 | 0.00000 |
| Max | 6.50774 | 6.46592 | 3.65630 | 3.96923 |
| Std. Dev | 4.20252 | 4.20231 | 0.80133 | 0.50349 |
| Skewness | -1.45906 | -1.45872 | 1.28785 | 7.62658 |
| Kortosis | 6.45932 | 6.45617 | 7.89583 | 48.7211 |

**Table 2**
Results of regression for time-varying movement.

| | RSP | RDO | ΔRCV | ΔDCV |
|---|---|---|---|---|
| *Ω* | *0.00000* | *0.00000* | *0.00000* | *0.00000* |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| *A* | *0.42306* ** | *0.36938* ** | *0.86860* ** | *0.86042* ** |
| | (0.2135) | (0.20041) | (0.17605) | (0.30020) |
| *B* | *0.57709* *** | *0.63072* *** | *0.13140* *** | *0.13964* *** |
| | (0.16158) | (0.16567) | (0.02297) | (0.03975) |
| *γ* | *0.01587* ** | *0.01144* *** | *0.00591* ** | *0.00564* ** |
| | (0.09313) | (0.09270) | (0.02534) | (0.03721) |
| *AIC* | *-712.8298* | *-662.5650* | *-553.1152* | *-722.0630* |
| *BIC* | *-688.0475* | *-637.7827* | *-528.3329* | *-697.2807* |
| *LL* | *415.4150* | *390.2830* | *335.5580* | *420.0320* |

Notes: Table 2 reports the regression results of time-varying movement between US stock markets and COVID-19, where AIC, BIC and LL are the Akaike's information criterion (AIC), Bayes' information criterion (BIC) and Levin and Lin statistics, respectively. The numbers in parenthesis correspond to standard deviation.
* , * *, and * ** refer to statistical significance at 1, 5, and 10 % levels, respectively.

functions pass the goodness to fit test.

First, the results show that there is significant asymmetric upper and lower tail dependence structure between the variations of daily reported COVID-19 cases and the S&P500 and Dow Jones markets. The upper tail dependence of the S&P500 and Dow Jones with the COVID-19 pandemic is higher than 2.0000, suggesting that the variations in daily COVID-19 cases exhibit positively significant upper tail dependence with the S&P500 and the Dow Jones. We have the following estimates for the S&P500: $\omega^U_{C,S_0}$ and $\omega^U_{C,S_1}$ are 2.80298 and 4.27328, but $\omega^L_{C,S_0}$ and $\omega^L_{C,S_1}$ are − 1.39686 and − 2.77882.

Fig. 3 plots the regime-switching lower left and upper right tail dependence. We can say that the S&P500 stock market shows significant regime-switching upper and lower tail dependence with COVID-19, and these higher and lower tail dependences present time-varying trends. Regarding the lower tail dependence stage, left and right tail dependence runs roughly between 0.8000 and 1.0000. However, for the higher tail dependence stage, left tail dependence runs roughly between 0.0000 and 0.0200, and right tail dependence runs roughly between 0.0020 and 0.0040. The positive values indicate that the S&P500 index suffers greater market

**Table 3**
Results of regression for regime switching time-varying dependence.

| | Daily reported COVID-19 cases | | Daily reported COVID-19 deaths | |
|---|---|---|---|---|
| | S&P500 | Dow Jones | S&P500 | Dow Jones |
| $\omega^U_{C,S_0}$ | *2.80298* | *4.33199* | *0.40104* | *4.40103* |
| | (0.00957) | (0.05682) | (0.00828) | (0.03585) |
| $\omega^U_{C,S_1}$ | *4.27328* | *3.48860* | *4.49272* | *5.10901* |
| | (0.01021) | (0.03425) | (0.02020) | (0.03603) |
| $\alpha_{C,U}$ | *-6.11470* | *-20.7616* | *-2.38375* | *-0.78761* |
| | (0.01885) | (0.02890) | (0.01925) | (0.02640) |
| $\beta_{C,U}$ | *-6. 04179* | *-17.5497* | *-17.2552* | *-18.8571* |
| | (0.02338) | (0.03956) | (0.02817) | (0.04578) |
| $\gamma_{C,U}$ | *-1.24960* | *-1.51062* | *-1.03008* | *-0.57866* |
| | (0.00932) | (0.01075) | (0.00847) | (0.00724) |
| $\omega^L_{C,S_0}$ | *-1.39686* | *-1.89551* | *-1.44582* | *-1.90580* |
| | (0.02103) | (0.03694) | (0.03320) | (0.03815) |
| $\omega^L_{C,S_1}$ | *-2.77882* | *-3.14332* | *-2.94909* | *-2.72063* |
| | (0.02629) | (0.04796) | (0.03436) | (0.04090) |
| $\alpha_{C,L}$ | *-3.01328* | *-2.73145* | *-7.51188* | *-12.8268* |
| | (0.02805) | (0.03239) | (0.02983) | (0.04509) |
| $\beta_{C,L}$ | *-2.92273* | *-10.4200* | *-3.85951* | *-8.01263* |
| | (0.02451) | (0.03015) | (0.02754) | (0.03768) |
| $\gamma_{C,L}$ | *-0.96704* | *-0.83981* | *-0.60720* | *-0.29247* |
| | (0.01393) | (0.01270) | (0.01135) | (0.01022) |
| $p_0$ | *0.99050* | *0.99050* | *0.99000* | *0.99000* |
| | (0.01729) | (0.01073) | (0.01514) | (0.01752) |
| $p_1$ | *0.99040* | *0.99060* | *0.99010* | *0.99040* |
| | (0.04106) | (0.04550) | (0.05171) | (0.05127) |
| *Log L* | *22.4420* | *21.1893* | *14.7787* | *22.1576* |
| *AIC* | *-45. 9894* | *-42.7193* | *-29.8376* | *-44.6230* |
| *SIC* | *-46.1347* | *-43.1884* | *-30.2235* | *-46.0469* |

Notes: Table 3 reports the regression results of switching time-varying dependence between US stock markets and COVID-19, where the AIC, BIC and Log L are the Akaike's information criterion (AIC), the Bayes' information criterion (BIC), and Log-likelihood, respectively. Standard errors are shown in parentheses.

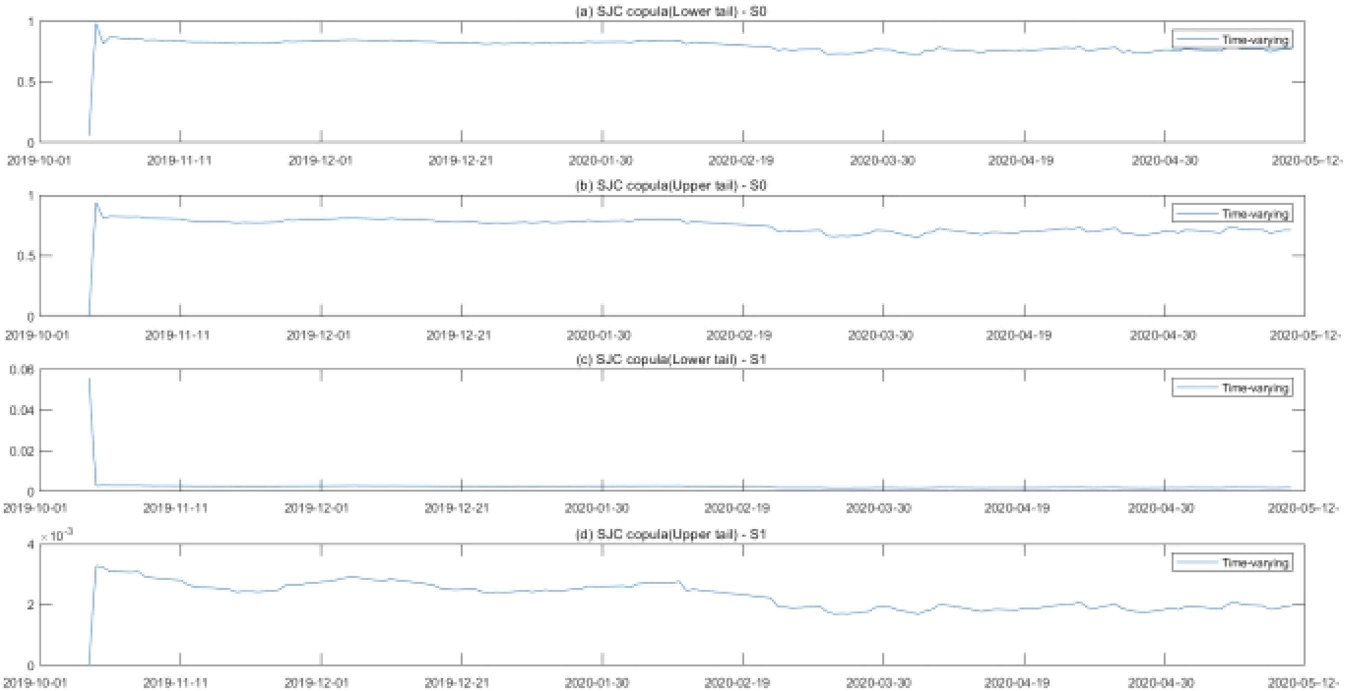


**Fig. 3.** The time varying lower and upper tail dependence between the S&P500 and daily reported COVID-19 cases.

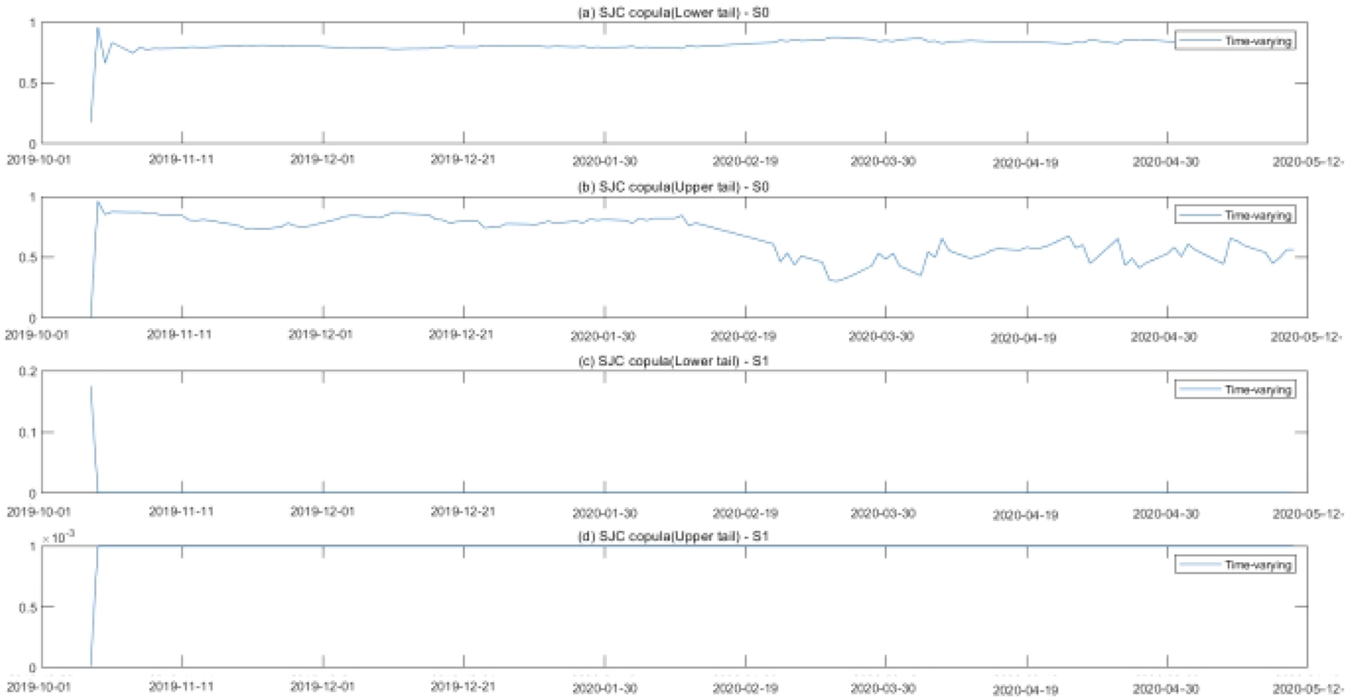


**Fig. 4.** The time varying lower and upper tail dependence between the Dow Jones and daily reported COVID-19 cases.

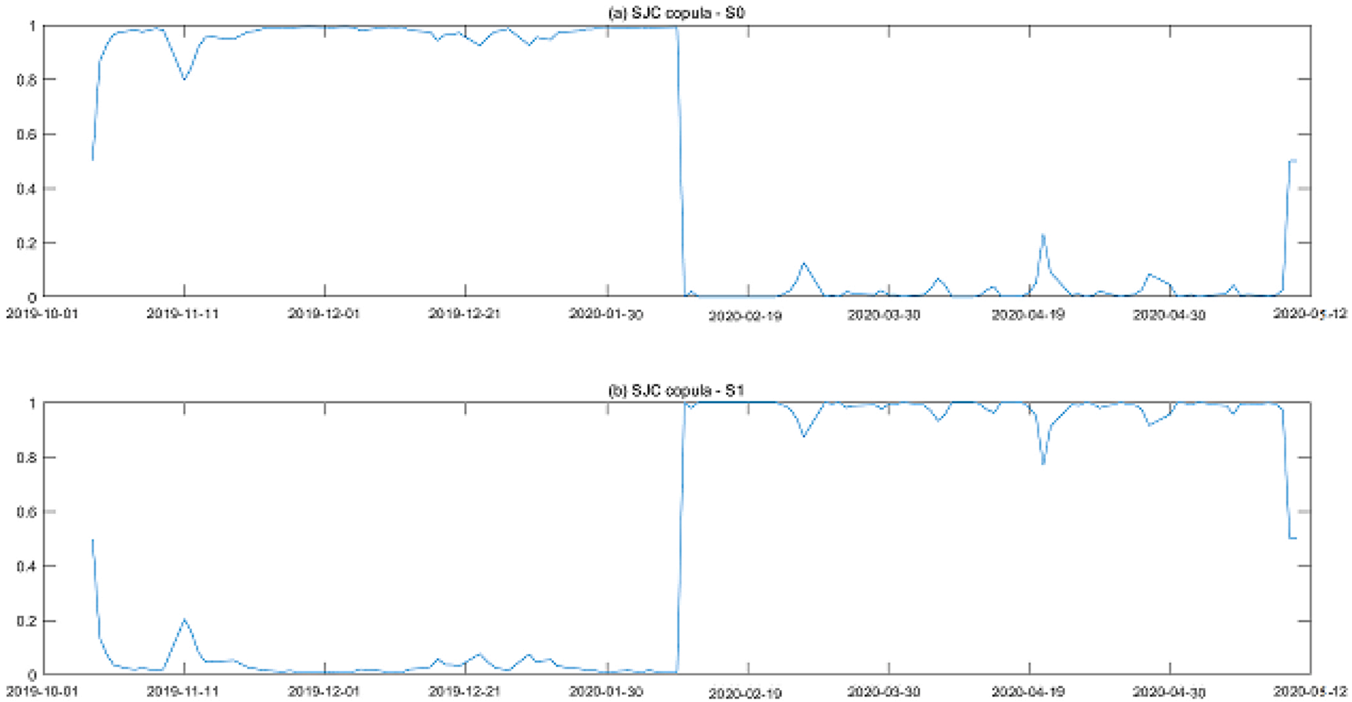


**Fig. 5.** The switching probabilities of regime switching time varying dependence between the S&P500 stock market and daily reported COVID-19 cases.

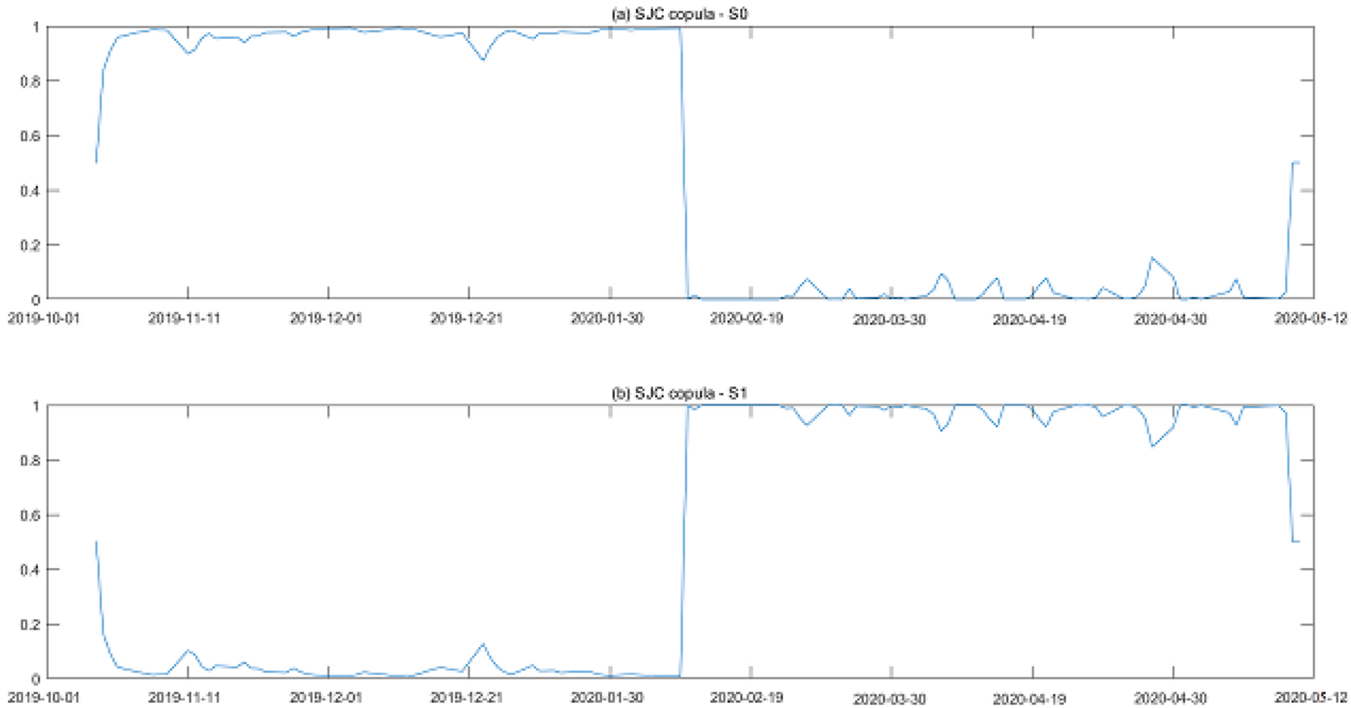


**Fig. 6.** The switching probabilities of regime switching time varying dependence between the Dow Jones and daily reported COVID-19 cases.

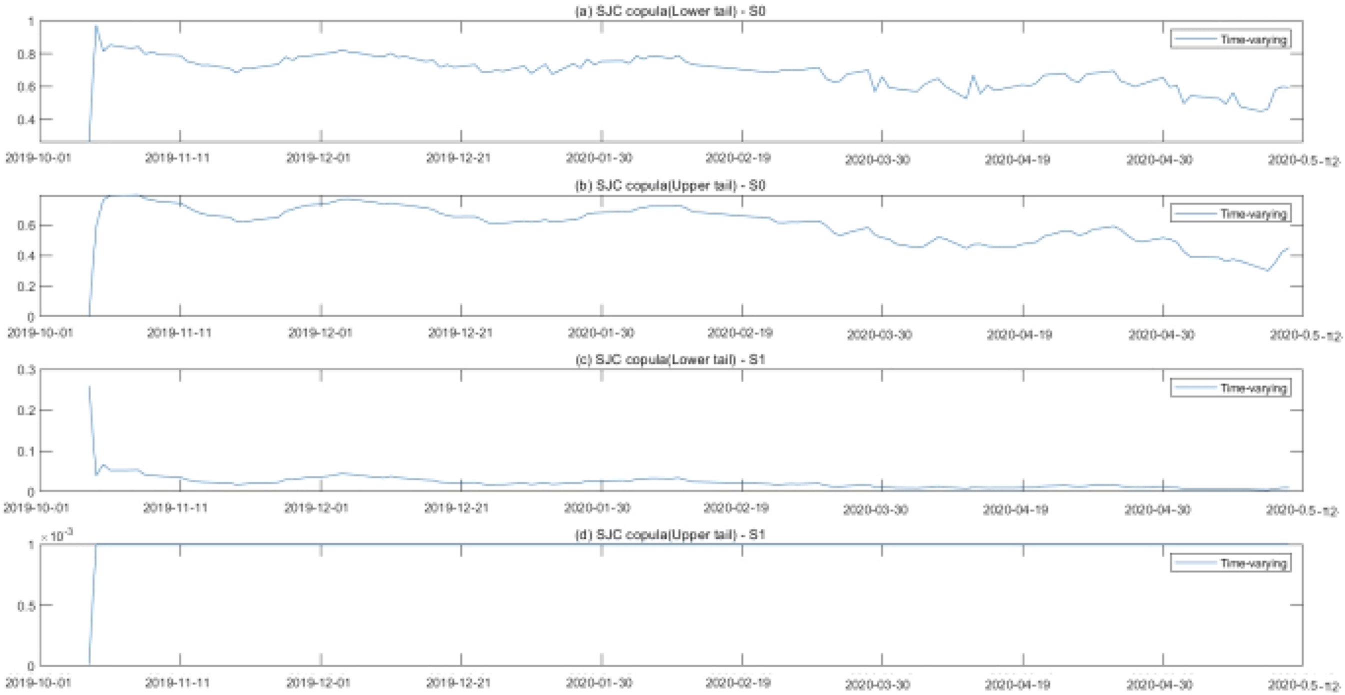


**Fig. 7.** The time varying lower and upper tail dependence between the S&P500 and daily reported COVID-19 deaths.

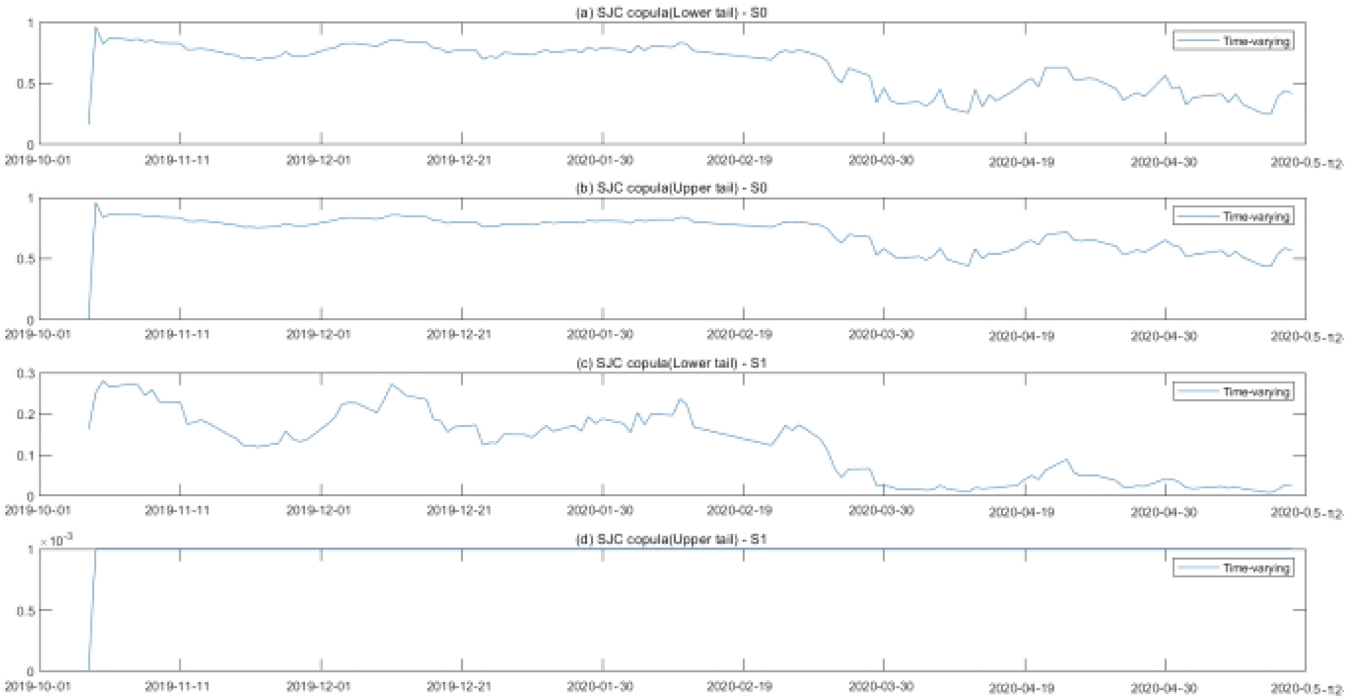


**Fig. 8.** The time varying lower and upper tail dependence between the Dow Jones and daily reported COVID-19 deaths.

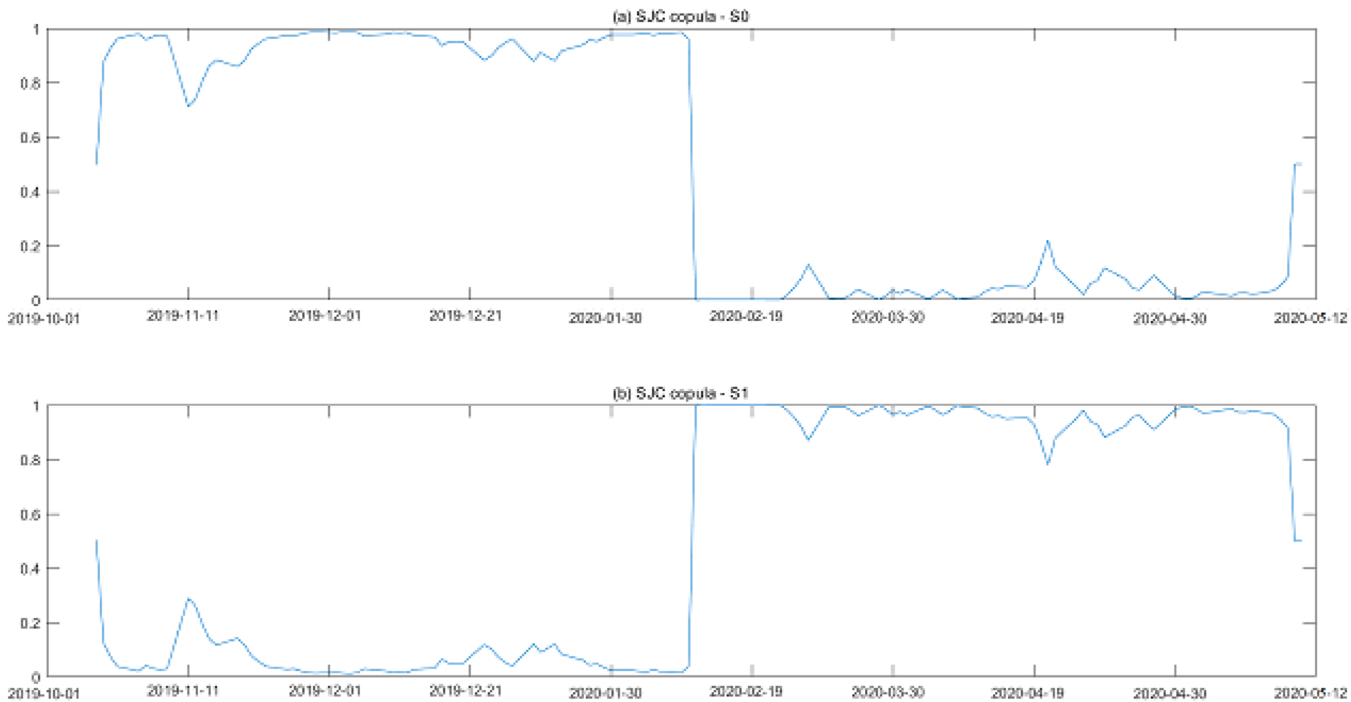


**Fig. 9.** The switching probabilities of regime switching time varying dependence between the S&P500 and daily reported COVID-19 deaths.

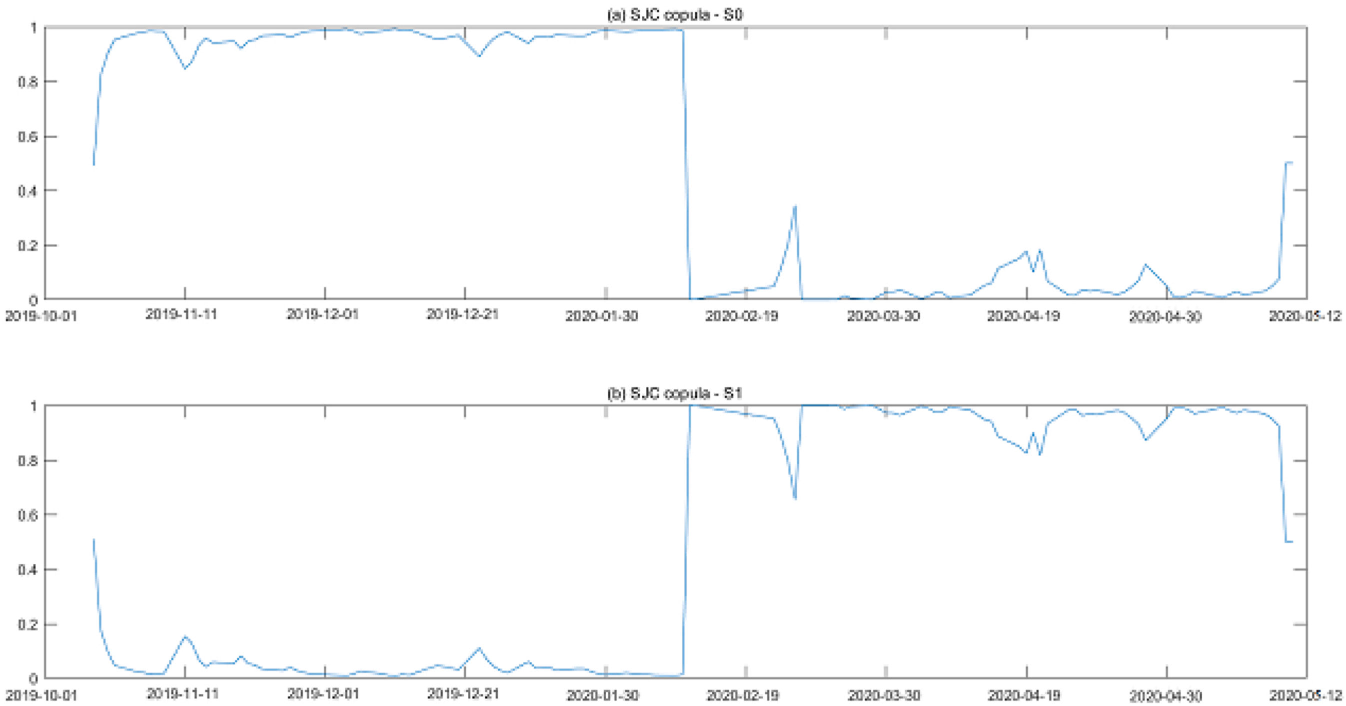


**Fig. 10.** The switching probabilities of regime switching time varying dependence between the Dow Jones and daily reported COVID-19 deaths.

shocks in the higher and lower tail dependence stage. The left tail dependence indicates that a decline in daily reported COVID-19 cases result in a greater decrease in the S&P500 stock index, and thus it is confirmed that the S&P500 presented significant regime-switching behaviour after the COVID-19 pandemic event began.

In the same way, there is significant regime-switching and time-varying upper and lower tail dependence between daily reported COVID-19 cases and the Dow Jones stock market. Fig. 4 presents the results of the lower and higher tail dependence stage, in which we observe that the variations of daily reported COVID-19 cases generate significant left and right tail dependence with the Dow Jones stock market. The coefficients also confirm that a rise or fall in daily reported COVID-19 cases led to a greater Dow Jones stock index increase (or decrease) in the higher and lower tail dependence stage.

The switching probabilities of regime switching time-varying dependence among daily reported COVID-19 cases and the US stock markets, i.e., the S&P500 and Dow Jones, are shown in Figs. 5 and 6. It is seen that both the S&P500 and the Dow Jones produce the regime switching time-varying dependence with daily reported COVID-19 cases. In particular, in the period after 19 January 2020, the switching probabilities of the remaining higher tail dependence jumped between 50 % and 100 %, and the switching probabilities of the remaining lower tail dependence ran between 0 % and 50 %.

Second, the results show a significant asymmetric lower and upper tail dependences between the variations of daily reported COVID-19 deaths and the S&P500 and Dow Jones stock markets. The upper right and lower left tail dependences present significant regime-switching and time-varying behaviours. We have absolute estimate values of $\omega^{U}_{C,S_1}$ and $\omega^{L}_{C,S_1}$ higher compared to that of $\omega^{U}_{C,S_0}$ and $\omega^{L}_{C,S_0}$ in the S&P500 and Dow Jones stock markets. Figs. 7 and 8 approve the coefficients' results, that is to say, for the higher and lower tail dependence stage, the variations of daily reported COVID-19 death cases provoke greater ranges in the S&P500 and Dow Jones indices. We find that the variations of daily reported COVID-19 deaths rise and fall together with the S&P500 and Dow Jones stock markets, but the difference in higher and lower tail dependence for the S&P500 is greater when compared to the difference for the Dow Jones during the study period. Also, we have the probabilities of the remaining lower and higher tail dependence being equal to roughly 99 %. All these findings imply that an increase in daily reported COVID-19 deaths results in sharp rises and falls of the S&P500 and Dow Jones indices.

Figs. 9 and 10 show the switching probabilities of the Markov switching time-varying dependence between daily reported COVID-19 deaths and the US stock markets. We note that in the period after 19 January 2020, both the S&P500 and Dow Jones stock markets induced significant regime-switching dynamic dependence, impacted by the COVID-19 pandemic. In particular, during the study period, a rise or fall in COVID-19 deaths led to a sharp increase or decrease in the S&P500 stock compared with the Dow Jones index.

## 6. Conclusion

The global public health emergency which emerged in the wake of the COVID-19 pandemic caused fluctuations in global stock and energy markets and uncertainty in global economic growth and trade volumes. As the largest economy in the world and with strong interconnectivity to other economies, the world's two largest stock markets (i.e., the Dow Jones and the S&P500 indices) in the US were adversely affected by the outbreak of COVID-19, experiencing a high contagion risk from Asia and Europe. The literature suggests that the US stock markets have an asymmetric association/dependence on both the sign and size of a stock market shock (in this study COVID-19). This paper therefore examined the asymmetric dependence structure between the S&P500 and the Dow Jones indices and the COVID-19 pandemic emergency using the Markov switching time-varying copula function. We investigated the dynamic behaviour of regime-switching between higher and lower tail dependences and time-varying dependence with upper and lower tail characteristics between the COVID-19 pandemic event and the US stock markets.

The findings of this paper, in general, reveal that the pandemic had significant and asymmetric time-varying left and right tail dependence with the US stock markets, exhibiting significant regime-switching behaviours with the higher and lower tail dependence characteristics. Further, these switching probabilities in the higher tail dependence stage were all greater compared to the lower tail dependence stage after 19 January 2020. Specifically, while the US stock indices had a left tail and leptokurtic distribution, daily reported COVID-19 cases and deaths had both right tail and leptokurtic distribution. We found that for the study period, the daily reported COVID-19 pandemic cases and deaths generated asymmetric upper and lower tail dependence in the S&P500 and Dow Jones indices as the upper and lower tail dependences induced significant regime-switching and time-varying characteristics. Furthermore, we observed that the daily reported COVID-19 cases and deaths produced positive upper tail dependences and negative lower tail dependences in the S&P500 and the Dow Jones indices. These results are better explained by the fact that for the lower tail dependence stage, a rise in the daily reported COVID-19 cases and deaths led the S&P500 and the Dow Jones stock to drop sharply for higher tail dependence compared than for lower tail dependence.

This paper makes a methodological contribution to the existing research by incorporating a combination of the Threshold Generalized Autoregression Conditional Heterogeneity (GJR-GARCH) model, the Markov regime-switching (MRS) model and the Symmetrized Joe-Clayton (SJC) copula function into the MRS time-varying SJC copula function to capture the regime-switching and time-varying dependence between the COVID-19 pandemic and the US stock markets (i.e., the S&P500 and the Dow Jones indices). To the best of the researchers' knowledge, no previous study has adopted such an approach. The paper also makes two contributions to the empirical literature by showing that: (a) the variations of the daily reported COVID-19 cases and cumulative COVID-19 deaths induced asymmetric lower (left) and upper (right) tail dependence with the US stock markets, and its left and right tail dependence exhibited significant time-varying trends; and (b) the left and right tail dependence between the US stock markets and the pandemic exhibited significant regime-switching behaviours, with its switching probabilities in the higher tail dependence stage all being greater than in the lower tail dependence stage after 1 December 2019. Given that "there will concomitantly be substantial financial market reaction

[when] there is a sudden appearance of a contagious respiratory illness or a new flaring of COVID-19″ (Goodell and Huynh, 2020, p.3), our findings could become a key reference point for policymakers and support them in their planning for responses to emergencies such as the COVID-19 pandemic.

The outcomes of this paper have vital implications for market participants and policymakers, i.e., investors, portfolio managers, corporations and governments, in addressing volatile market situations and predicting market risks during significant events such as the COVID-19 pandemic. This research, in particular, has important implications for portfolio managers in terms of how to benefit from trading in volatile times during crisis periods and how to achieve better portfolio diversification. Future research on the basis of longer time-series would help researchers to verify the robustness of the findings of this study.

## Author statement

All authors are agreed to publish this paper, they checked and approved. Authors have no conflict of interest.

## Declaration of Competing Interest

The authors declare no conflict of interest.

## Data Availability

Data will be made available on request.

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