Hindawi
Complexity
Volume 2022, Article ID 8137932, 9 pages
https://doi.org/10.1155/2022/8137932

*Research Article*

# Economic Policy Uncertainty and Conditional Dependence between China and U.S. Stock Markets

**Xinyu Wu, Meng Zhang, Mengqi Wu, and Hao Cui**

*School of Finance, Anhui University of Finance and Economics, Bengbu 233030, China*

Correspondence should be addressed to Xinyu Wu; xywu@aufe.edu.cn

Received 5 November 2021; Revised 21 December 2021; Accepted 23 December 2021; Published 7 January 2022

Academic Editor: Paulo Jorge Silveira Ferreira



In this paper, we investigate the impact of economic policy uncertainty (EPU) on the conditional dependence between China and U.S. stock markets by employing the Copula-mixed-data sampling (Copula-MIDAS) framework. In the case of EPU, we consider the global EPU (GEPU), the American EPU (AEPU), and the China EPU (CEPU). The empirical analysis based on the Shanghai Stock Exchange Composite (SSEC) index in China and the S&P 500 index in the U.S. shows that the tail dependence between China and U.S. stock markets is symmetrical, and the *t* Copula outperforms alternative Copulas in terms of in-sample goodness of fit. In particular, we find that the *t* Copula-MIDAS model with EPU dominates the traditional time-varying *t* Copula in terms of in-sample fitting. Moreover, we observe that both the GEPU and AEPU have a significantly positive impact on the conditional dependence between China and U.S. stock markets, whereas CEPU has no significant impact. The tail dependence between China and U.S. stock markets exhibits an increasing trend, particularly in the recent years.

## 1. Introduction

The economic activities of many countries and regions are intertwined due to the financial globalization. Financial globalization plays an important role in global economic growth, which not only facilitates the international capital flow but also promotes the deployment of global resources. However, financial turbulence intensifies as economic and financial globalization develops, putting the financial system's stability under great strain. Financial crises have erupted frequently since the 1990s and spread quickly from one market to another. The subprime mortgage crisis in the U.S. in 2008, for example, swiftly spread to Europe and East Asia, wreaking havoc on global economic growth.

In recent years, the Chinese financial market has experienced rapid development and played an increasingly vital role in the world economy, which enhanced its dependence with other countries' financial markets. Because the U.S. is the world's largest economy with the highest financialization, it is critical to investigate the conditional dependence between China and U.S. stock markets.

Numerous studies have provided evidence that economic policy uncertainty (EPU) in various countries is interrelated (see, e.g., [1, 2]). In particular, Jiang et al. [3] showed that there is a close interrelationship between the policy uncertainties of U.S. and China, and the interrelationship is mostly affected by bilateral trade, exchange rate, and investor sentiment. Moreover, many researchers have investigated the relation between EPU and international stock markets (see, e.g., [4–7]). Li and Peng [8] found that American EPU will lead to changes in the co-movements of China stock market with U.S. stock market. Further, Li et al. [9] showed that the American EPU affects China stock market in the long term. Zhang et al. [10] found that China's global influence has increased, but the U.S. has maintained its dominance.

Since 2016, the global black swan events such as the Brexit, the U.S. interest rate hike, the U.S.-China trade war, and the COVID-19 pandemic have affected global stock markets significantly, which has forced governments around the world to make frequent changes to their policies in order to limit the economic impact of these events. As a result, the current level of EPU is at extremely elevated levels. The issue of whether the high EPU is likely to affect the conditional dependence between China and U.S. stock markets requires immediate research, as it has important implications for investors, regulators, and risk managers.

The rest of the paper is organized as follows. In Section 2, we present a literature review. Section 3 describes the methodology, including the marginal distribution model, the Copula-MIDAS framework, and the estimation method. Section 4 describes the data. Section 5 presents the empirical results. Section 6 concludes the paper.

## 2. Literature Review

The study of the correlation between international stock markets has attracted a great deal of attention in the literature. Many previous studies use the co-integration test, VAR model, and Granger causality test to investigate the correlation between the stock markets (see, e.g., [11–13]). However, considering the weak autocorrelation and conditional heterogeneity of stock market returns, it is unreasonable to use traditional regression approach, since it imposes the strong conditions of independent homogeneity. To overcome this problem, Engle [14] proposed a simple class of multivariate GARCH models referred to as dynamic conditional correlation, which is capable of capturing linear correlation between stock markets. In practice, however, the correlation between the stock markets is nonlinear, suggesting that it is unreasonable to use traditional linear models to describe the dependence structure between the stock markets. As a result, the Copula approach is suggested, which has been widely used in the literature for describing the nonlinear dependence structures. In fact, the Copula approach provides a general framework and can better capture the tail dependence. Ning [15] used the Copula to investigate the symmetrical tail dependence between the stock and foreign exchange markets. Aloui et al. [16, 17] constructed a Copula-GARCH model to explore the conditional dependence between the crude oil price, the U.S. dollar exchange rate, and the natural gas price.

As the static Copula approach cannot capture the time-varying correlation between the data, some scholars suggested the time-varying Copula approach. Manner and Reznikova [18] provided a survey over existing Copula models allowing for time-varying dependencies that have been proposed in recent years. Reboredo [19] investigated the correlation between crude oil markets using the time-varying Copula approach. Wang et al. [20] used the time-varying Copula model to explore the dependence structure between Chinese and other major world economies' stock markets. Wu et al. [21] suggested that dynamic Student's $t$ Copula is superior to static Student's $t$ and other dynamic Copulas when exploring the correlation between oil prices and exchange rates. Jammazi et al. [22] investigated the dynamic dependence between the stock and long-term government bond returns over the past two decades using the time-varying Copula approach.

Recently, several scholars incorporated low-frequency macrovariables into the Copula framework to explore if macrofactors have an impact on the dependence structure between financial markets. In particular, Gong et al. [23, 24] developed a Copula-mixed-data sampling (Copula-MIDAS) model to investigate the impact of macrofundamentals, market uncertainty, and liquidity on the interdependence of Chinese stock and bond markets. Jiang et al. [25] constructed a TVM-Copula-MIDAS model to explore the interdependence between Chinese stock, bond, and fund markets. The model considers the impact of exogenous explanatory variables on dynamic dependence.

However, to the best of our knowledge, there are few studies to investigate the impact of EPU on the conditional dependence between China and U.S. stock markets. Against this backdrop, this paper aims to investigate how EPU affects the conditional dependence between China and U.S. stock markets. To do so, we employ the Copula-MIDAS framework and the EPU index proposed by Baker et al. [26], which is constructed based on newspapers' coverage frequency. Specially, for the EPU, we consider the global EPU (GEPU), the American EPU (AEPU), and the China EPU (CEPU). We investigate how different EPU indices affect the conditional dependence between China and U.S. stock markets.

## 3. Methodology

*3.1. Marginal Distribution Model.* The Copula approach allows us to separately specify models for marginal distributions. Thus, we have a lot of flexibility in selecting marginal distribution models. Considering the characteristics of the conditional heteroscedasticity of stock market returns, this paper employs the popular GARCH model to model and fit the return series. The GARCH model can be written as

$$\begin{aligned} r_t &= \mu + \varepsilon_t, \\ \varepsilon_t &= \sigma_t z_t, \quad z_t \sim N(0,1), \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \end{aligned} \tag{1}$$

where $r_t$ is the return, $\mu$ is the conditional mean of the return, which is usually set to 0, $\sigma_t^2$ is the conditional variance of the return, $\epsilon_t$ is the return innovation, and $z_t$ is the standardized return innovation.

*3.2. Copula.* The Copula is a multivariate marginal distribution function, which describes a flexible dependence structure between two variables and is commonly referred to as a connection function or dependence function. According to Sklar's theorem, for a joint distribution function, the marginal distributions and the dependence structure represented by a Copula function can be separated. Let $r_{1t}$ and $r_{2t}$ be the SSEC index return and S&P 500 index return, respectively. We assume that $r_{1t}$ and $r_{2t}$ are modeled by the GARCH model presented in Section 3.1. The standardized return innovations are obtained as $z_{1t}$ and $z_{2t}$. We assume that the conditional cumulative distribution functions of $z_{1t}$ and $z_{2t}$ are $F_1(z_{1t})$ and $F_2(z_{2t})$, respectively, which are estimated via their empirical cumulative distribution functions $\widehat{F}_1(z_{1t})$ and $\widehat{F}_2(z_{2t})$. Also, the joint distribution function of $z_{1t}$ and $z_{2t}$ is $H(z_{1t}, z_{2t})$. Then, according to Sklar's theorem, there exists a Copula function $C(.,.)^2 \longrightarrow [0, 1]$ such that

$$H(z_{1t}, z_{2t}) = C(u_t, v_t\theta), \tag{2}$$

where $u_t = \widehat{F}_1(z_{1t})$ and $v_t = \widehat{F}_2(z_{2t})$ follow (0, 1) uniform distribution and $\theta$ is the dependence parameter of the Copula. Therefore, for any multidimensional distribution $H$, it can be divided into marginal distributions $F_i$ and a Copula function.

The Copula has good modeling characteristics, which is able to describe the tail dependence between the variables in extreme cases. It can describe the upper-tail dependence and the lower-tail dependence. The upper-tail dependence coefficient $\lambda^U$ and the lower-tail dependence coefficient $\lambda^L$ are defined as

$$\begin{aligned}
\lambda^U &= \lim_{u \longrightarrow 1^-} \text{Prob}\left[F_2(z_{2t}) \geq u | F_1(z_{1t}) \geq u\right] \\
&= \lim_{u \longrightarrow 1^-} \frac{1 - 2u + C(u, u|\theta)}{1 - u}, \\
\lambda^L &= \lim_{u \longrightarrow 0^+} \text{Prob}\left[F_2(z_{2t}) \leq u | F_1(z_{1t}) \leq u\right] \\
&= \lim_{u \longrightarrow 0^+} \frac{C(u, u|\theta)}{u}.
\end{aligned} \tag{3}$$

If $\lambda^L(\lambda^U) = 0$, i.e., the lower (upper) tail dependence coefficient is equal to zero, there is no lower (upper) tail dependence. Also, if $\lambda^L(\lambda^U) \in (0, 1]$, there is a lower (upper) tail dependence. Commonly used Copula functions are the binary normal Copula function, binary $t$ Copula function, binary Archimedes Copula function, i.e., the Gaussian Copula, Student-$t$ Copula, Gumbel Copula, Survival Gumbel Copula, Clayton Copula, and Survival Clayton Copula, which are presented in Table 1.

As can be seen from Table 1, the Gaussian Copula cannot describe the tail dependence, while the Student-$t$ Copula can describe the symmetrical tail dependence but cannot describe the asymmetric dependence. The Gumbel Copula and Survival Clayton Copula can only describe the upper-tail dependence, but not the lower-tail dependence. The Survival Gumbel Copula and Clayton Copula can describe the lower-tail dependence rather than the upper-tail dependence.

*3.3. Copula-MIDAS.* In this paper, we aim to investigate the impact of EPU on the conditional dependence between China and U.S. stock markets. As the frequency of EPU index (monthly) is different from that of the U.S. and China stock market returns (daily), the traditional Copula approach cannot be used for our purpose. In order to solve the mixed-frequency data problem, this paper employs the Copula-MIDAS model that can directly incorporate EPU index into the dynamic process of the dependence structure.

The Copula-MIDAS model can be written as

$$(u_t, v_t) \sim C(u_t, v_t|\theta_t), \theta_t = \Psi(\lambda_t), \tag{4}$$

$$\lambda_t = C_\tau + \beta\lambda_{t-1} + \alpha\frac{1}{S}\sum_{s=1}^{S}\left[F_1^{-1}(u_{t-s})F_2^{-1}(v_{t-s})\right], \tag{5}$$

$$C_\tau = \overline{c} + \gamma\sum_{k=1}^{K_c}\phi_k(\omega_c)EPU_{\tau-k}, \tag{6}$$

where $\text{EPU}_t$ denotes the GEPU, AEPU, or CEPU, which may affect the dependence between the China and U.S. stock markets, and $\Psi(\cdot)$ is an appropriate transformation function to ensure that the parameter always remains in its domain.

The basic idea of the Copula-MIDAS model is to decompose the dependence structure described by Copula into long-term and short-term components using the MIDAS approach, which is similar to that of GARCH-MIDAS model.

In equation (5), we assume that $|\beta| < 1$, which ensures that $\lambda_t$ is a stationary process. The lag order $S$ is determined by the Akaike information criterion (AIC) and Schwarz information criterion (SC).

In equation (6), the long-term trend of $\lambda_t$, $C_\tau$, is modeled by smoothing the monthly variable $\text{EPU}_\tau$ in the spirit of MIDAS regression approach. $K_c$ is the number of MIDAS lags. Following Colacito et al. [27], the weighting function $\phi_k(\omega_{p,c})$ is chosen as the beta polynomial function:

$$\phi_k(\omega_c) = \frac{(1 - i/K_c)^{\omega_c - 1}}{\sum_{i=1}^{K_c}(1 - i/K_c)^{\omega_c - 1}}. \tag{7}$$

To implement the Copula and Copula-MIDAS models, we adopt a two-step procedure for the estimation, namely, the inference functions for the margins (IFM) method by Joe and Xu [28]. This method breaks the estimation into two steps. To be specific, in the first step, the marginals are obtained by estimating the GARCH model via the quasi-maximum likelihood method. In the second step, given the estimated marginal functions, we estimate the parameters of the Copula via the quasi-maximum likelihood method.

## 4. Data

For our empirical analysis, we use the daily returns of the SSEC index and the S&P 500 index for the sample period from January 4, 2005, to January 5, 2021, resulting in a total of 3770 observations. The data were obtained from the Wind Database. For the EPU indices, we choose the GEPU, AEPU, and CEPU, for the sample period from January 2005 to January 2021, resulting in a total of 192 monthly data.

Table 2 presents the descriptive statistics of the daily SSEC and S&P 500 index returns as well as the monthly GEPU, AEPU, and CEPU indices. As can be seen from Table 2, the means of the SSEC and S&P 500 index returns are larger than zero, indicating that the two stock markets have positive returns in the long term. Comparing the standard deviations

Table 1: Copula functions.

| | $\lambda^L$ | $\lambda^U$ |
|---|---|---|
| Gaussian Copula | 0 | 0 |
| Student-$t$ Copula | $2t_{\nu+1}(-\sqrt{\nu+1}\cdot\sqrt{1-\theta}/\sqrt{1+\theta})$ | $2t_{\nu+1}(-\sqrt{\nu+1}\cdot\sqrt{1-\theta}/\sqrt{1+\theta})$ |
| Gumbel Copula | 0 | $\lambda^U = 2-2^{1/\theta}$ |
| Survival Gumbel Copula | $\lambda^L = 2-2^{1/\theta}$ | 0 |
| Clayton Copula | $\lambda^L = 2^{1/\theta}$ | 0 |
| Survival Clayton Copula | 0 | $\lambda^U = 2^{1/\theta}$ |

Table 2: Descriptive statistics of daily SSEC and S&P 500 index returns as well as monthly GEPU, AEPU, and CEPU indices.

| | SSEC | S&P 500 | GEPU | AEPU | CEPU |
|---|---|---|---|---|---|
| Mean | 0.0003 | 0.0003 | 145.2330 | 127.0769 | 150.5792 |
| Min. | −0.1276 | −0.1378 | 48.8196 | 57.2026 | 23.7000 |
| Max. | −0.1378 | 0.1096 | 429.5147 | 350.4598 | 661.8000 |
| Std. | 0.0164 | 0.0129 | 72.9342 | 49.5498 | 114.4801 |
| Skewness | −0.6053 | −0.7226 | 1.2406 | 1.3154 | 1.9207 |
| Kurtosis | 8.3226 | 19.0593 | 4.4544 | 5.5353 | 6.9297 |
| JB | 4681.6772 | 40851.1529 | 66.1778 | 106.7857 | 241.5982 |

*Note*. Std. denotes the standard deviation, and JB denotes the Jarque–Bera statistics.

of the SSEC index and S&P 500 index returns, we can observe that China stock market has a higher volatility than the U.S. stock market. The skewness and kurtosis of the index returns reveal that the two return series exhibit a leptokurtic and heavy-tailed distribution. In addition, it can be seen from the Jarque–Bera statistics that the return series do not follow the normal distribution. The means for the EPU indices from high to low are CEPU, GEPU, and AEPU, implying that Chinese government makes more frequent changes to its economic policies than others.

Figure 1 presents the time series plots of the daily SSEC index and S&P 500 index returns. It is obvious that the two return series exhibit well-known behaviors of volatility clustering. Figure 2 plots the monthly GEPU, AEPU, and CEPU indices. As can be seen from Figure 2, the GEPU, AEPU, and CEPU exhibit an increasing trend, particularly in recent years.

## 5. Empirical Results

In this section, we present the empirical results. In Section 5.1, we present the estimation results for the marginal distribution model and obtain the standardized residual (return innovation) series. In Section 5.2, various static Copulas are compared based on the empirical cumulative distribution functions computed from the standardized residual (return innovation) series, and the best fitting Copula is selected. In Section 5.3, we employ the Copula-MIDAS framework based on the best fitting Copula to investigate the impact of EPU (including the GEPU, AEPU, and CEPU) on the dynamic tail dependence between China and U.S. stock markets.

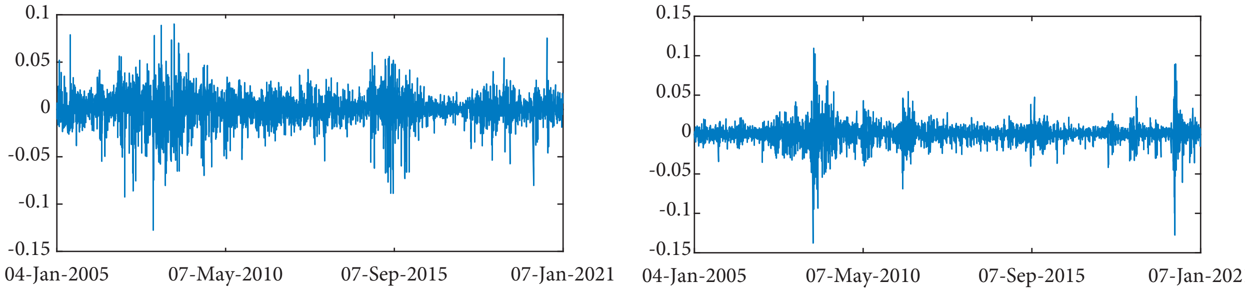
*5.1. Estimation Results for Marginal Distribution Model.* Before modeling the index returns, the ARCH test is conducted. The ARCH test results are presented in Table 3. It can be seen from Table 3 that the ARCH effects for both the SSEC and S&P 500 index returns are significant, suggesting that the index returns should be modeled by the GARCH model.

Table 4 presents the parameter estimation results for the marginal distribution model, namely, the GARCH model. As can be seen from the table, the estimates of the persistence coefficient, $\alpha+\beta$, are close to 1, suggesting that the volatilities of China and U.S. stock markets exhibit high persistence. In particular, we find that the volatility persistence of China stock market is higher than that of U.S. stock market.

Based on the parameter estimation results reported in Table 4, we obtain the standardized residual (return innovation) series, which are presented in Figure 3. Figure 4 presents the QQ plots of the standardized residuals $z_{1t}$ and $z_{2t}$. It is clear that the residuals do not follow the standard normal distribution. Thus, to estimate the marginal distributions, we use the empirical cumulative distribution functions of the standardized residuals $z_{1t}$ and $z_{2t}$, which are presented in Figure 5.

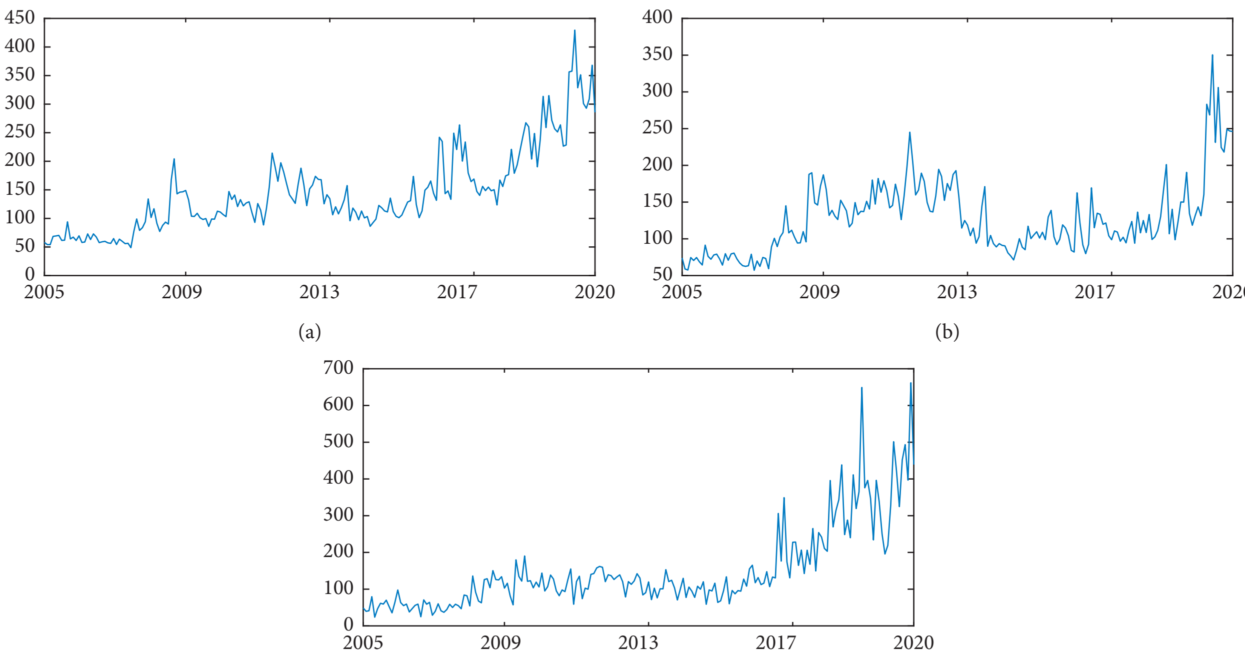
*5.2. Estimation Results for Static Copulas.* Based on the estimated marginals, various static Copulas are estimated via the quasi-maximum likelihood method. The estimation results of various Copulas are reported in Table 5. It can be seen from Table 5 that the parameter estimates of various Copulas are significant, indicating that there is a certain correlation between China and U.S. stock markets. In particular, we find that the Student-$t$ Copula is the best fitting Copula for describing the dependence between China and U.S. stock markets in terms of the Log-lik and AIC values.

*5.3. Estimation Results for Dynamic Student-t Copulas.* To capture the dynamic dependence between China and U.S. stock markets, the dynamic Copula approach should be




(a) (b)

Figure 1: Daily SSEC index and S&P 500 index returns. (a) SSEC: return $r_{1,t}$. (b) S&P 500 return: $r_{2,t}$.




(c)

Figure 2: Monthly GEPU, AEPU, and CEPU indices. (a) Global EPU. (b) American EPU. (c) Chinese EPU.

Table 3: ARCH test results for the SSEC index and S&P 500 index returns.

| | Name | Value | Standard error | $t$ statistic | $P$ value |
|---|---|---|---|---|---|
| SSEC | Constant | $1.1105e-06$ | $3.2666e-07$ | 3.3997 | 0.0007 |
| | ARCH (1, 1) | 0.06033 | 0.0037 | 16.4860 | $4.6519e-61$ |
| S&P 500 | Constand | $2.7209e-06$ | $4.0015e-07$ | 6.7997 | $1.0482e-11$ |
| | ARCH (1, 1) | 0.1399 | 0.0085 | 16.3910 | $2.2015e-6$ |

used. Traditionally, the time-varying Copula model is used. In the time-varying Copula model, we have

$$\lambda_t = \omega + \beta\lambda_{t-1} + \alpha\frac{1}{S}\sum_{s=1}^{S}\left[F_1^{-1}(u_{t-s})F_2^{-1}(v_{t-s})\right]. \tag{8}$$

It should be noted that in the time-varying Copula model, the EPU cannot be incorporated. As a consequence, the traditional time-varying Copula model cannot capture the impact of EPU on the correlation between China and U.S. stock markets.

In this section, we compare the time-varying Copula model to the Copula-MIDAS model incorporating EPU for describing the tail dependence between China and U.S. stock markets. The specific Copula is chosen as the best fitting Copula, i.e., Student-$t$ Copula. Estimation results for the two types of dynamic Student-$t$ Copulas, the time-varying Student-$t$ Copula and the Student-$t$ Copula-MIDAS, are presented in Table 6.

Table 4: Estimation results for the marginal distribution model.

| | $\mu$ | $\omega$ | $\beta$ | $\alpha$ | Log-lik |
|---|---|---|---|---|---|
| SSEC | 0.0003<br>(0.0002) | $1.1081E-06$<br>($3.1475E-07$) | 0.9388<br>(0.0029) | 0.0599<br>(0.0036) | $1.0696e+04$ |
| S&P 500 | 0.0006<br>(0.0001) | $3.0093E-06$<br>($4.1251E-07$) | 0.8297<br>(0.0097) | 0.1491<br>(0.0094) | $1.2234e+04$ |

*Note*. The number in parenthesis is the standard error.

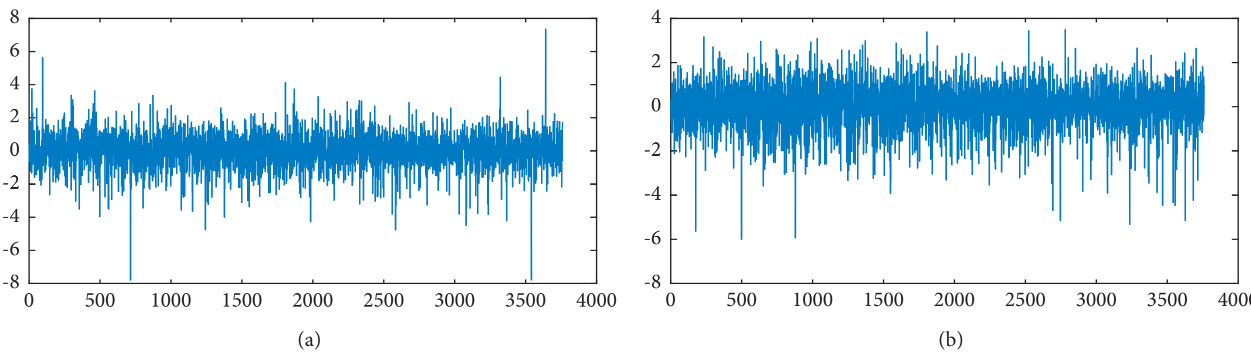


Figure 3: Standardized residual series for the SSEC index and S&P 500 index returns. (a) $z_{1t}$. (b) $z_{2t}$.

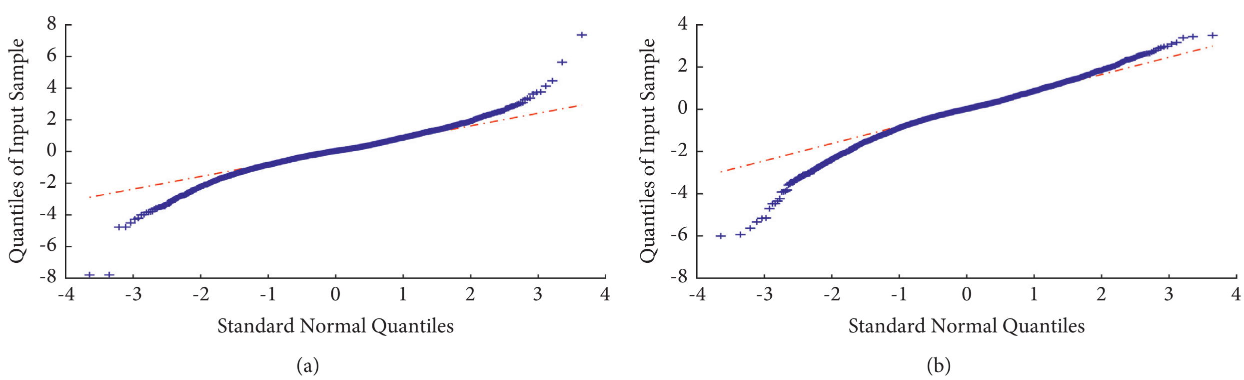



Figure 4: QQ plots of the standardized residuals $z_{1t}$ and $z_{2t}$. (a) QQ plot of $z_{1t}$. (b) QQ plot of $z_{2t}$.

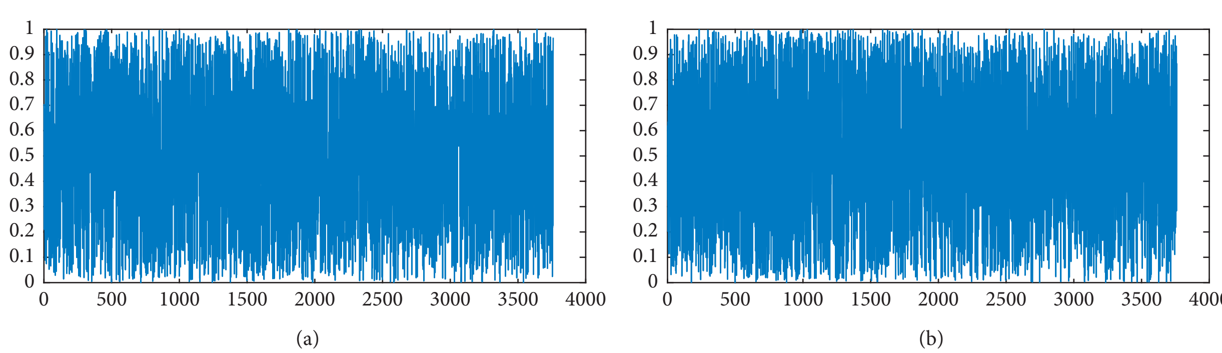


Figure 5: Marginal distributions of $z_{1t}$ and $z_{2t}$. (a) Marginal distribution of $z_{1t}$ ($u_t$). (b) Marginal distribution of $z_{2t}$ ($v_t$).

Table 5: Estimation results for various Copulas.

| | Gaussian | Student-$t$ | Gumbel | Survival Gumbel | Clayton | Survival Clayton |
|---|---|---|---|---|---|---|
| $\theta$ | 0.1191<br>(0.0160) | 0.1165<br>(0.0166) | 1.0627<br>(0.0113) | 1.0651<br>(0.0110) | 0.1250<br>(0.0198) | 0.1099<br>(0.0199) |
| $\nu$ | | 31.1864<br>(17.5890) | | | | |
| Log-lik | 26.7349 | 28.4350 | 19.6637 | 27.5177 | 24.8943 | 18.1982 |
| AIC | −51.4698 | −52.8700 | −37.3274 | −52.0123 | −47.7887 | −34.3964 |

*Note*. Log-lik denotes the log likelihood, and AIC denotes the Akaike information criterion.

Table 6: Estimation results for dynamic Student-$t$ Copulas.

| | Time-varying Student-$t$ Copula | Student-$t$ Copula-MIDAS | | |
|---|---|---|---|---|
| | | GEPU | AEPU | CEPU |
| $\omega$ | 0.0011<br>(0.0022) | 1.1433<br>(0.5502) | 1.6545<br>(1.2871) | 1.0295<br>(0.3407) |
| $\alpha$ | 0.0105<br>(0.0066) | 0.0899<br>(0.1235) | −0.0063<br>(0.1582) | 0.0107<br>(0.0157) |
| $\beta$ | 1.9930<br>(0.0255) | −1.8775<br>(0.2469) | −1.8647<br>(0.4247) | 1.7766<br>(0.3783) |
| $\nu$ | 3.4362<br>(0.6345) | 3.4456<br>(0.6308) | 3.4917<br>(0.6598) | 3.5096<br>(0.6692) |
| $\bar{c}$ | | −2.5240<br>(0.7195) | −2.6225<br>(0.9822) | −0.1229<br>(0.2000) |
| $\gamma$ | | 0.6162<br>(0.1499) | 0.6478<br>(0.2078) | 0.0320<br>(0.0522) |
| Log-lik | 31.8951 | 36.3791 | 33.5023 | 38.4785 |

*Note*. Log-lik represents the log likelihood.

As can be seen from Table 6, compared to the time-varying Student-$t$ Copula model, the Student-$t$ Copula-MIDAS model with EPU indices yields higher log-likelihood values, indicating that the EPU affects the correlation between China and U.S. stock markets. The positive estimates of the coefficient $\gamma$ suggest that EPU has a positive impact on the conditional tail dependence of China and U.S. stock markets. It should also be noted that the estimates of coefficient $\gamma$ for the GEPU and AEPU are significant, while they are not significant for the CEPU, suggesting that both the GEPU and AEPU have significant impacts on the correlation between China and U.S. stock markets, while CEPU has no significant impact. The possible explanation is that although China's influence in the world economy is growing, as an emerging market, it is difficult for China's economic policies to influence the U.S. stock market. Therefore, the correlation between China and U.S. stock market will be more significantly affected by GEPU and AEPU.

Figure 6 presents the estimated tail dependences from the Student-$t$ Copula-MIDAS model with GEPU, AEPU, and CEPU. It is clear that the tail dependence between China and

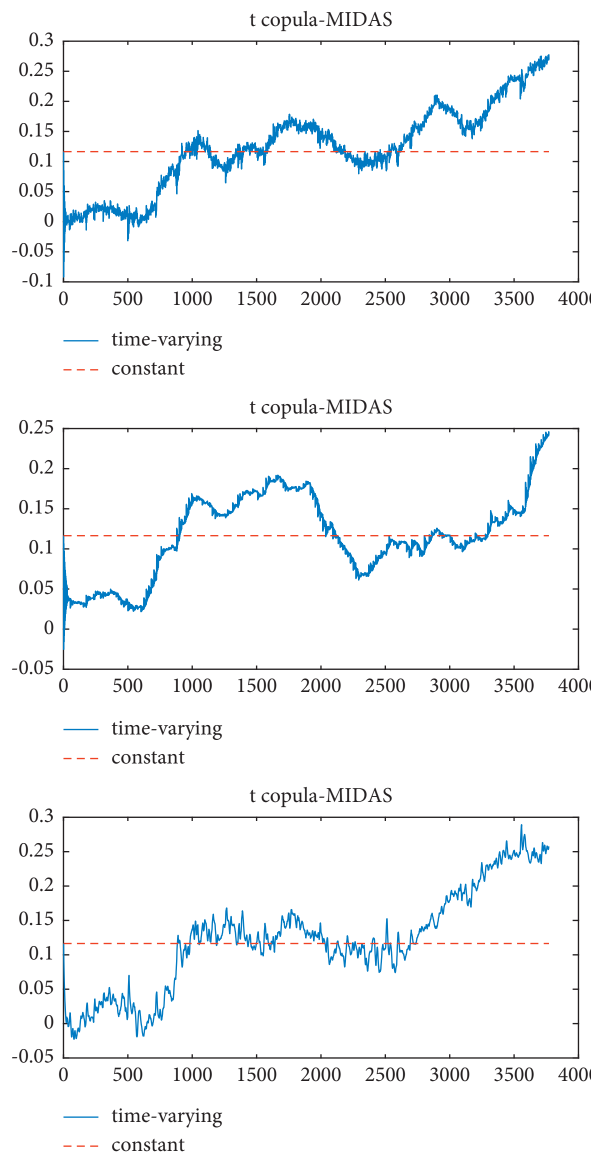



Figure 6: Estimated tail dependences from Student-$t$ Copula-MIDAS model with GEPU, AEPU, and CEPU.

U.S. stock markets varies greatly over time, indicating that the extreme risk between China and U.S. stock markets is changing dynamically. In particular, we observe that the tail dependence between China and U.S. stock markets exhibits an increasing trend, particularly in recent years.

## 6. Conclusions

This paper employs the Copula-MIDAS framework to investigate the impact of EPU on the tail dependence between China and the U.S. stock markets. For the EPU, we consider the GEPU, AEPU, and CEPU. Our empirical results demonstrate that the tail dependence between China and U.S. stock markets is symmetrical, and the $t$ Copula outperforms alternative static Copulas in terms of in-sample goodness of fit. In particular, we find that the $t$ Copula-MIDAS model with EPU dominates the traditional time-varying $t$ Copula in terms of in-sample fitting. Moreover, we observe that both the GEPU and AEPU have a significantly positive impact on the conditional dependence between China and U.S. stock markets, whereas CEPU has no significant impact. The tail dependence between China and U.S. stock markets exhibits an increasing trend, particularly in recent years.

It is worth pointing out that the approach adopted in the paper could be extended. While the simple GARCH model is used as the marginal distribution model in the paper, it would be interesting to use the realized GARCH model instead of the GARCH model, which exploits the intraday high-frequency data. This would lead to a better fitting result. Moreover, future research could extend our work by investigating the role of EPU in risk management and portfolio decision using the Copula-MIDAS approach. We leave these for future research.

## Data Availability

The data on the SSEC index of China and the S&P 500 index of the U.S. were obtained from Wind Database of China, and the data on the monthly EPU indices were obtained from https://www.policy.uncertainty.com/. All the data are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## Acknowledgments

This research was supported by the National Natural Science Foundation of China (no. 71971001), the University Natural Science Research Project of Anhui Province (no. KJ2019A0659), the Anhui University Collaborative Innovation Project (no. GXXT-2021-078), the Southern Jiangsu Capital Markets Research Center (no. 2017ZSJD020), and the Innovative Research Project for Graduates of Anhui University of Finance and Economics (no. ACYC2020123).

## References

[1] A. Bonaime, H. Gulen, and M. Ion, "Does policy uncertainty affect mergers and acquisitions?" *Journal of Financial Economics*, vol. 129, no. 3, pp. 531–558, 2018.

[2] N. Biljanovska, F. Grigoli, and M. Hengge, "Fear thy neighbor: spillovers from economic policy uncertainty," *Review of International Economics*, vol. 29, no. 2, pp. 409–438, 2021.

[3] Y. Jiang, Z. Zhu, G. Tian, and H. E. Nie, "Determinants of within and cross-country economic policy uncertainty spillovers: evidence from US and China," *Finance Research Letters*, vol. 31, pp. 195–206, 2019.

[4] L. Pástor and P. Veronesi, "Uncertainty about government policy and stock prices," *The Journal of Finance*, vol. 67, no. 4, pp. 1219–1264, 2012.

[5] L. Pástor and P. Veronesi, "Political uncertainty and risk premia," *Journal of Financial Economics*, vol. 110, no. 3, pp. 520–545, 2013.

[6] M. Arouri, C. Estay, C. Rault, and D. Roubaud, "Economic policy uncertainty and stock markets: long-run evidence from the US," *Finance Research Letters*, vol. 18, pp. 136–141, 2016.

[7] T. C. Chiang, "Economic policy uncertainty, risk and stock returns: evidence from G7 stock markets," *Finance Research Letters*, vol. 29, pp. 41–49, 2019.

[8] X. Li and L. Peng, "US economic policy uncertainty and co-movements between Chinese and US stock markets," *Economic Modelling*, vol. 61, pp. 27–39, 2017.

[9] R. Li, S. Li, and D. Yuan, "Does economic policy uncertainty in the US influence stock markets in China and India? Time-frequency evidence," *Applied Economics*, vol. 52, no. 39, pp. 4300–4316, 2020.

[10] D. Zhang, L. Lei, and Q. Ji, "Economic policy uncertainty in the US and China and their impact on the global markets," *Economic Modelling*, vol. 79, pp. 47–56, 2019.

[11] C. Diks and V. Panchenko, "A new statistic and practical guidelines for nonparametric Granger causality testing," *Journal of Economic Dynamics and Control*, vol. 30, no. 9-10, pp. 1647–1669, 2006.

[12] B. Zhang and X. M. Li, "Has there been any change in the comovement between the Chinese and US stock markets?" *International Review of Economics & Finance*, vol. 29, pp. 525–536, 2014.

[13] B. Güloğlu, P. Kaya, and R. Aydemir, "Volatility transmission among Latin American stock markets under structural breaks," *Physica A: Statistical Mechanics and Its Applications*, vol. 462, pp. 330–340, 2016.

[14] R. Engle, "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models," *Journal of Business & Economic Statistics*, vol. 20, no. 3, pp. 339–350, 2002.

[15] C. Ning, "Dependence structure between the equity market and the foreign exchange market? a Copula approach," *Journal of International Money and Finance*, vol. 29, no. 5, pp. 743–759, 2010.

[16] R. Aloui, M. S. A. Ben, and D. K. Nguyen, "Conditional dependence structure between oil prices and exchange rates: a copula-GARCH approach," *Journal of International Money and Finance*, vol. 32, pp. 719–738, 2013.

[17] R. Aloui, M. S. B. Aïssa, S. Hammoudeh, and N. Khuong, "Dependence and extreme dependence of crude oil and

natural gas prices with applications to risk management," *Energy Economics*, vol. 42, pp. 332–342, 2014.
[18] H. Manner and O. Reznikova, "A survey on time-varying Copulas: specification, simulations, and application," *Econometric Reviews*, vol. 31, no. 6, pp. 654–687, 2012.
[19] J. C. Reboredo, "How do crude oil prices co-move?: a Copula approach," *Energy Economics*, vol. 33, no. 5, pp. 948–955, 2011.
[20] K. Wang, Y. H. Chen, and S. W. Huang, "The dynamic dependence between the Chinese market and other international stock markets: a time-varying Copula approach," *International Review of Economics & Finance*, vol. 20, no. 4, pp. 654–664, 2011.
[21] C. C. Wu, H. Chung, and Y. H. Chang, "The economic value of co-movement between oil price and exchange rate using Copula-based GARCH models," *Energy Economics*, vol. 34, no. 1, pp. 270–282, 2012.
[22] R. Jammazi, A. K. Tiwari, and R. Ferrer, "Time-varying dependence between stock and government bond returns: international evidence with dynamic Copulas," *The North American Journal of Economics and Finance*, vol. 33, pp. 74–93, 2015.
[23] Y. Gong, Q. Chen, and J. Liang, "A mixed data sampling copula model for the return-liquidity dependence in stock index futures markets," *Economic Modelling*, vol. 68, pp. 586–598, 2018.
[24] Y. Gong, R. Bu, and Q. Chen, "What affects the relationship between oil prices and the US stock market? A mixed-data sampling copula approach," *Journal of Financial Econometrics*, 2020.
[25] C. Jiang, X. Ding, and Q. Xu, "A TVM-Copula-MIDAS-GARCH model with applications to VaR-based portfolio selection," *The North American Journal of Economics and Finance*, vol. 51, pp. 101–074, 2020.
[26] S. R. Baker, N. Bloom, and S. J. Davis, "Measuring economic policy uncertainty," *Quarterly Journal of Economics*, vol. 131, no. 4, pp. 1593–1636, 2016.
[27] R. Colacito, R. F. Engle, and E. Ghysels, "A component model for dynamic correlations," *Journal of Econometrics*, vol. 164, no. 1, pp. 45–59, 2011.
[28] H. Joe and J. J. Xu, *The Estimation Method of Inference Functions for Margins for Multivariate Models*The University of British Columbia, Vancouver, Canada, 1996.