Global Risk and Safe Haven Currency: Copula-DCC Approach*

Masao Kumamoto[1] and Juanjuan Zhuo[2]

[1]Graduate School of Business Administration, Hitotsubashi University, Tokyo, Japan

[2]Faculty of Humanities and Social Sciences, Kochi University, Kochi, Japan

Abstract

In this paper, we employ the Copula-Dynamic Conditional Correlation approach to investigate the safe-haven currency status of eight currencies as well as gold and Bitcoin against the main stock markets. Based on the properties of the estimated dynamic conditional correlations, we classify the currencies into a diversifier, a hedge and a safe haven currency. We also employ the threshold approach to investigate whether market uncertainty measured by the VIX would have significant effects on the estimated dynamic conditional correlation. This analysis is closely related to the study of contagion. We find that the CHF and gold are the strong hedges against the U.S. stock market except for the European sovereign crisis period, and the JPY and Bitcoin have hedge and /or safe currency status. We also find that the degrees of the role of Bitcoin as a hedge currency, and roles of the JPY and gold as a hedge and/or safe haven currency are not affected by the increase in market uncertainty, while that of the CHF as a hedge currency would be weakened as market uncertainty increases.

Keywords: Safe haven currency, Bitcoin, Contagion, Copula-DCC, Threshold

JEL Classification: F31, G15

---

* This work was performed in the Cooperative Research Project of the Mizuho Securities Co., Ltd. and Hitotsubashi University on “Monetary Economy and the FinTech”. We acknowledge gratefully the stimulated discussion in the meetings held at Mizuho Securities Co., Ltd. on 1st October 2018 and 29th March 2019, and funding from Mizuho Securities Co., Ltd..

1. Introduction

Since the global financial crisis in 2007-2009, the global economic risks stemming from economic or political uncertainties have increased markets' risk aversion and disrupted financial markets intermittently[2]. These global economic risks, for example, include the Greek sovereign crisis in 2010 which led to the European sovereign crisis in 2011 (euro crisis), the Federal Reserve's announcement of future tapering of its policy of quantitative easing in 2013 (taper tantrum), Chinese stock market turbulence in 2015 (China shock) , the exit of the United Kingdom from the European Union in 2016 (Brexit), the United States presidential election in 2016, and the trade dispute between the United States and China since 2018.

In parallel with the widespread fear of the global economic risks, studies of safe-haven currencies have been receiving increasing attention. According to Kaul and Sapp (2006), a safe haven currency is defined as a currency which behaves like a hedge for a reference portfolio of risky assets conditional on movements in global risk aversion. Namely, a safe haven currency appreciates, when global risk aversion increases, and the value of the reference portfolio of risky assets decreases. The study of the dependence between foreign exchange markets and other financial markets, especially, stock markets is important for policymakers and international portfolio managers who are concerned about financial contagion.

Ranaldo and Söderlind (2009) investigate a safe haven currency status of five currencies (the CHF, the DEM, the EUR, the JPY, and the GBP) against the USD over the 1993 to 2008 period, and find that the JPY, the CHF, the EUR, and the GBP behave as safe-haven currencies. They also find that safe haven currency status behaves non-linearly. De Bock and de Carvalho Filho (2013) find that the JPY and the CHF are the only two currencies that appreciate against the U.S. dollar during financial market turbulence.

---

[2] World Economic Forum (WEF) (2019) defines a "global risk" as an uncertain event or condition that, if it occurs, can cause significant negative impact for several countries or industries within the next 10 years. WEF classifies global risk into economic, environmental, geopolitical, societal and technological risks. As for the economic global risks, they include (i) asset bubbles in a major economy, (ii) failure of a major financial mechanism or institution, (iii) failure/shortfall of critical infrastructure, (iv) fiscal crises in key economies, (v) high structural unemployment or underemployment, (vi) illicit trade, (vii) severe energy price shock and (viii) unmanageable inflation.

Fatum and Yamamoto (2016) investigate intra-safe haven currency, namely, which safe haven currency is the safest during the recent global financial crisis. They use the implied volatility of S&P 500 options (VIX) as an indicator of market uncertainty, and consider seven currencies which are often regarded as the safe-haven currency (the USD, the JPY, the CHF, the EUR, the GBP, the SEK, and the CAD). Subsequently, they employ the threshold analysis developed by Hansen (2000) to investigate whether the intra-safe haven currency behavior changes when market uncertainty increases above threshold levels. They find that the JPY is the “safest” currency and that only the JPY appreciates as market uncertainty increases.

Masujima (2017) investigates the safe haven status of the JPY, the CNY (onshore renminbi), the CNH (offshore renminbi), other Asian currencies (the Korean won, the Indonesia rupiah, and the Singapore dollar), and alternative assets (gold and Bitcoin). He calculates a safe-haven index, which measures the movement of each exchange rate to a change in market uncertainty as measured by the VIX. He shows that the JPY has the safe-haven status, while the CNH had the safe-haven status in early 2010 but has lost its status. The Korean won and the Indonesia rupiah tends to be vulnerable, while the Singaporean dollar has signaled the early sign for the safe-haven status.

Some literatures attempt to explain what makes safe-haven currency. Fratzscher (2009) finds that countries with low foreign exchange reserves, weak current account positions and high direct financial exposure vis-à-vis the United States depreciated the most during the crisis. Habib and Stracca (2012) investigate the determinants of safe-haven currencies. They follow the discussion by Brunnermeier *et al*. (2008) that returns on low-interest rate currencies tend to appreciate when global risk goes up, while high-interest rate currencies tend to depreciate sharply, which mean that low-interest rate currencies are safe havens in financial turmoil. Thus, after controlling for the effects of the carry trade, they find that only a few factors such as the net foreign asset position, the stock market capitalization, and the self-fulfilling prophecies (whether currencies have been a good hedge in the past), are the fundamentals of safe-haven currency. As for the interest rate spread, it is associated with a safe-haven status only during the global financial crisis from 2007-2009. Moreover, they find the non-linearity characteristics, as the impact of the fundamentals is stronger in the crisis than in normal times.

The aim of this paper is to investigate the safe-haven currency status of main currencies and investigate its relationship with global risks measured by the VIX, which is similar to the previous literature reviewed above. However, there are some departures from them.

First, unlike previous studies which investigate whether the exchange rate would appreciate or depreciate when global risk aversion increases, we focus on the correlation between the movements of exchange rates and the return of stock indices, which may be crucial information when building an efficient portfolio. According to Baur and Lucey (2010), Ratner and Chiu (2013), and Bouri et al. (2017), financial assets can be classified into three main categories: a diversifier, a hedge, and a safe haven. A diversifier is an asset that is weakly and positively correlated with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average. A weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset during times of stress. Following the above definitions, we investigate the asset correlation and identify the type of each asset.

Second, we employ a copula-Dynamic Conditional Correlation (copula-DCC) approach to investigate the correlation. One popular approach for calculating the dynamic conditional correlation between two asset returns is to employ the DCC model introduced by Engle (2002). However, the DCC model is estimated under the assumption of multivariate normality, while this assumption is unrealistic. For example, it is well known that the correlation between stock returns is higher in a bear or a high volatility regime than in a bull or a low-volatility regime, meaning the existence of asymmetric dependence structures. Considering the context of our study, where the realized value in the area of left tail of a given stock price index distribution means a sharp decrease in stock prices, while the realized value in the area of right tail of a given exchange rate (defined by the price of one unit of the currency in terms of the USD) distribution means a sharp appreciation of the currency, the higher dependence between the left tail of the stock price index and the right tail of the exchange rate may be interpreted as a safe haven status. However, a normal distribution cannot capture such an asymmetric dependence. These problems can be treated easily by using copulas. The concept of copula was introduced by Sklar (1959). A copula is defined as a function which provides a mapping between the marginal distribution of each univariate series and the multivariate distribution of all series. It implies that there is no need to require that the marginal distribution and the multivariate distribution must follow the same type of distribution as in the DCC model. Therefore, copula can capture the dependence structure in the tails of the distribution, which is a primary interest in our study[3].

Third, we investigate the contagion effect by using the threshold approach. Forbes and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock to one country or group of countries. Therefore, under the situation that two markets have a high degree of co-movement during tranquil periods, even if the markets remain to display a high degree of co-movement after a shock to one of them, this may not mean contagion. This situation is regarded as interdependence. Namely, interdependence can be defined as a long-run dependence between markets. On the other hand, contagion is a short-run phenomenon that occurs in the period of financial crises, which can cause a statistically significant increase in correlation known as “correlation breakdown”. In our context, if there exists a threshold value above which the VIX has statistically significant effects on the estimated dynamic correlation, it can be interpreted as the evidence of “correlation breakdown”, namely, contagion.

Forth, we extend the candidates for safe-haven currencies to eight currencies, the AUD, the CAD, the CNY, the EUR, the JPY, the SEK, the CHF, and the GBP. Moreover, as with Masujima (2017), we include gold and Bitcoin. As pointed out by Baur *et al*. (2018), Bitcoin is often named “new gold”, because it shares some crucial characteristics with gold such as the verifiable scarcity through mining (limited supply and growth), the non-centrality (a decentralized peer-to-peer payment system) and independence from central banks or government authorities. Due to these characteristics, Bitcoin might have a

---

[3] Patton (2006), Jondeau and Rockinger (2006), Rodriguez (2007) and Peng and Ng (2011) employ the copula approach for the application of analyzing the dependence structure.

safe haven status when the financial system and market are disrupted.

The remainder of this paper is organized as follows. Section 2 and 3 discuss the empirical methods and data, respectively. Section 4 presents the results. Finally, the last section concludes the study.

2. Empirical Methods

As the first step, we investigate the asset correlation by using the copula-DCC approach.

We assume that the $n \times 1$ vector $Y_t \equiv [\Delta e_{1,t}, \cdots \Delta e_{n-1,t}\ , \Delta s_t]'$ follows the VAR(p) model,

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + u_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + D_t \varepsilon_t \,, \tag{1}$$

where $\Delta e_{i,t}$ is the first difference in the log of the spot exchange rate which is defined by the price of one unit of currency $i = 1, \cdots, n-1$ in terms of the USD. Thus, the positive value of $\Delta e_{i,t}$ means the appreciation of currency i. Δs_t denotes the first difference in the log of the stock price index.

As in the case of the DCC model of Engle (2002), let H_t be an $n \times n$ covariance matrix and decompose it into

$$H_t = D_t R_t D_t \,, \tag{2}$$

where D_t is an $n \times n$ diagonal matrix of time-varying standard deviations with $\sqrt{h_{i,t}}$ ($i = 1, \cdots, n$) as the ith element of the diagonal, $D_t = diag\left(\sqrt{h_{1,t}}, \cdots, \sqrt{h_{n,t}}\right)$. We will obtain D_t by assuming that the conditional variance $h_{i,t}$ follows the univariate Exponential GARCH(1, 1) model. This assumption is based on the empirically stylized fact that negative shocks at time $t-1$ have a stronger impact on the variance at time t than positive shocks, which is called as the leverage effect,

$$\ln h_{i,t} = \alpha_i + \beta_i \ln h_{i,t-1} + \gamma_i \varepsilon_{i,t-1} + \delta_i \left(\left| \varepsilon_{i,t-1} \right| - E \left| \varepsilon_{i,t-1} \right| \right) \tag{3}$$

R_t is an $n \times n$ symmetric time-varying correlation matrix,

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}, \tag{4}$$

where Q_t is defined as the following exponential smoother equation, which is used solely to provide R_t,

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \tag{5}$$

where $\bar{Q}$ denotes the unconditional covariance matrix of the standardized residuals.

We model the joint distribution of the standardized residuals vector $D_t^{-1}u_t$ by using copulas[4]. Let x_i ($i = 1.\cdots, n$) be a random variable with a marginal distribution function F_i ($i = 1.\cdots, n$). Each multivariate distribution $F(x_1, \cdots, x_n)$ can be represented as its marginal distribution function by using a copula such as

$$F(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F(x_n)) \tag{6}$$

An n-dimensional copula C determined in $[0,1]^n$ for distributions F can be defined by

$$C(u_1, \cdots, u_n) = F(F_1^{-1}(x_1), \cdots, F_n^{-1}(x_n)) \quad \text{for} \quad u_i \in [0,1], \quad i = 1.\cdots, n \tag{7}$$

Then, the density functions of F and C are given by

$$f(x_1, \cdots, x_n) = c(F_1(x_1), \cdots, F(x_n)) \prod_{i=1}^{n} f_i(x_i) \tag{8}$$

$$c(u_1, \cdots, u_n) = \frac{f(F_1^{-1}(u_1), \cdots, F_n^{-1}(u_n))}{\prod_{i=1}^{n} f_i(F_i^{-1}(u_i))} \tag{9}$$

where f_i are the marginal densities and F_i^{-1} are the quantile function of the margins. For example, the density of the Normal (Gaussian) copula is defined by

$$c(u_1, \cdots, u_n; R_t) = \left| R_t \right|^{-\frac{1}{2}} e^{-\frac{1}{2}u'(R_t' - I)u} \tag{10}$$

where I is the identity matrix. The density of the Student-t copula with shape parameter τ is defined by

---

[4] The following discussions are based on Kim and Jung (2016).

$$c(u_1,\cdots,u_n;R_t,\tau)=\left|R_t\right|^{-\frac{1}{2}}\frac{\Gamma\left(\frac{\tau+n}{2}\right)\Gamma\left(\frac{\tau}{2}\right)^n\left(1+\frac{1}{\tau}t_\tau^{-1}(u)'R_t^{-1}t_\tau^{-1}(u)\right)^{-\frac{\tau+n}{2}}}{\left\{\Gamma\left(\frac{\tau+n}{2}\right)^n\right\}^n\Gamma\left(\frac{\tau}{2}\right)\prod_{i=1}^{n}\left(1+\frac{(t_\tau^{-1}(u_i))^2}{\tau}\right)^{-\frac{\tau+1}{2}}} \tag{11}$$

where $t_\tau^{-1}(\cdot)$ is the quantile function.

We test the fit of four typical copulas, namely, Normal, Student-t, Clayton and Gumbel copulas, and select the family which best fits the data by using the Akaike's Information Criterion (AIC). As for the marginal distribution, we select it as the empirical distribution based on the non-parametric method.

As the second step, we investigate the contagion effect by using the threshold approach developed by Hansen (2000). In the concrete, we regress the estimated dynamic conditional correlation on the proxy of market uncertainty, the VIX. If the VIX has statistically significant effects on the estimated dynamic conditional correlation, but threshold does not exist, it means that the degree of the role of the currency as a diversifier or hedge changes as the market uncertainty changes. If there exist thresholds above which the VIX has statistically significant effects on the estimated dynamic correlation, it can be interpreted as the evidence of "correlation breakdown", namely, contagion. Otherwise, if the VIX does not have statistically significant effects and/or there are no threshold effects, it can be regarded as the interdependence when the correlations are high on average, or no-interdependence when the correlations are close to zero on average.

We specify the estimation equation as follows:

$$dcc_{is,t}=\alpha_i+\beta_i\ln vix_t+\delta_i dcc_{is,t-1}+\varepsilon_{i,t}\text{, if threshold does not exist}$$

$$\begin{aligned} dcc_{is,t} &= \alpha_i+\beta_{1,i}\ln vix_t I(\theta_0<\ln vix_t\le\theta_1)+\cdots \\ &\quad +\beta_{m+1,i}\ln vix_t I_{m+1}(\theta_m<\ln vix_t\le\theta_{m+1})+\delta_i dcc_{is,t-1}+\varepsilon_{i,t} \quad \text{, otherwise} \\ &= \alpha_i+\sum_{j=1}^{m+1}\beta'_{j,i}\ln vix_t I(\theta_{j-1}<\ln vix_t\le\theta_j)+\delta_i dcc_{is,t-1}+\varepsilon_{i,t} \end{aligned} \tag{12}$$

with m thresholds and m+1 regions, where j indicates the regions, and $I(\theta_{j-1}<\ln vix_t\le\theta_j)$ is an indicator for the jth region. $dcc_{is,t}$ stands for the estimated dynamic conditional correlation between currency i and the stock price index. θ_j is a threshold parameter to be estimated and the estimator is given by

$$\hat{\theta}_j = \arg\min_{\theta_j \in \Gamma_j} S_{T_1}\left(\theta_j \middle| \hat{\theta}_1, \cdots, \hat{\theta}_{j-1}\right), \text{ for } \Gamma_j = (\theta_0, \theta_{m+1}) \text{ excluding } \hat{\theta}_1, \cdots, \hat{\theta}_{j-1}, \quad (13)$$

where $S_{T_j}\left(\theta_j \middle| \hat{\theta}_1, \cdots, \hat{\theta}_{j-1}\right) = \sum_{t=2}^{T}\{dcc_{is,t} - \alpha_i - \sum_{j=1}^{m+1} \beta'_{ji} \ln vix_t \, I_j(\theta_{j-1} < \ln vix_t \leq \theta_j) - \delta_i dcc_{is,t-1}\}^2$ is the minimum sum of squared residuals (SSR) conditional on the j-1 estimated thresholds. The optimal number of thresholds is based on the Bayesian Information Criterion (BIC), which is defined based on SSR from the fitted model as $BIC = T\ln(SSR/T) + \kappa \ln(T)$, where κ is the number of parameters in the model.

3. Data

In this paper, we choose eight currencies as candidates for the safe haven currencies: the AUD, the CAD, the CNY, the EUR, the JPY, the SEK, the CHF, and the GBP. Moreover, we consider gold and Bitcoin. Exchange rates are defined as the price of one unit of each currency in terms of the USD. Thus, the increase in exchange rates means appreciation. Needless to say, we recognize that the USD would be a candidate for a safe-haven currency. As pointed out by Habib and Stracca (2012), one paradoxical aspect of the global financial crisis was the appreciation of the USD as a safe haven currency although the US was an origin of the crisis. However, in this paper, we use the USD as a *numeraire* currency. As for gold, we use the price of gold in terms of the USD in the London Bullion Market. As for the stock price indices, we consider four indices: MSCI World, U.S., Europe, and Pacific indices.

Our sample period basically runs from 3 January 2000 to 31 December 2019. However, the sample period for the CNY is from 21 July 2005, when People's Bank of China announced the adoption of a managed floating exchange rate regime under which the exchange rate would be managed in relation to a basket of currencies. For Bitcoin, the sample period starts from 29 April 2013 due to data availability issues.

The data for exchange rates, gold price, and stock indices are sourced from *Datastream*. The data for the VIX are obtained from CBOE, and the data for Bitcoin come from CoinMarketCap.

Table 1(a) provides descriptive statistics of the first difference in the log of eight exchange rates, the prices of gold and Bitcoin, and four stock price indices, except for VIX which appears in the actual value. From the table, we can see that the standard deviation of the CNY is relatively small, reflecting the managed floating exchange rate regime. On the other hand, the average, the range and the standard deviation of Bitcoin are quite larger than those of other currencies and stock price indices. Table 1 (b) provides unconditional correlations, and we can see that the JPY is negatively correlated with the World, U.S. and Europe indices, the CHF is negatively correlated with the U.S. index, and the Bitcoin is negatively correlated with all stock price indices. Moreover, World, U.S., and Europe indices are highly correlated with each other.

<Insert Table 1(a), (b) >

4.Empirical Results

Table 2 shows the results of the selection of copulas. We test four typical copulas, Normal, Student-t, Clayton, and Gumbel copulas, and select the best-fitted family based on the AIC for each pair of the exchange rate (including gold and Bitcoin) with the stock price index.

We can see that most of the pairs are well described by Student-t Copula. Figure 1 displays the scatter plot of four copulas, in which two random variables (x_1, x_2) are generated so that Kendall's rank correlation coefficient τ （Kendall's τ） equals to 0.75, where Kendall's τ is defined as,

$$\Pr\left\{(x_1^i - x_1^j)(x_2^i - x_2^j) > 0\right\} - \Pr\left\{(x_1^i - x_1^j)(x_2^i - x_2^j) < 0\right\}.$$

If the condition $x_1^i > x_1^j$ and $x_2^i > x_2^j$ is always satisfied, then $\tau = 1$. On the other hand, if the condition $x_1^i > x_1^j$ and $x_2^i < x_2^j$ is always satisfied, then $\tau = -1$.

By comparing Figure 1 (a) and (b), we can see that Student-t copula can capture better dependence between extreme values, namely tail dependence than Normal copula. Moreover, the events near the area of (0,1) or (1,0) can occur more frequently under Student-t copula than Normal copula, which means that when one variable would take an extreme value, another variable can take an extreme value in opposite direction more frequently.

As for the CNY, Normal copula is selected. This might be because a managed floating exchange rate regime has been adopted in China so that the fluctuations in the CNY has been stable regardless of the movements in the stock markets. Bitcoin displays unique properties. For example, Gumbel copula rotated 270 degrees is selected for the pair with World index, and Clayton copula rotated 90 degrees is selected for the pair with Pacific index. In general, Clayton copula captures strong dependence around the lower left area, while Gumbel copula captures strong dependence around the upper right area. Therefore, as displayed in Figure 1 (c) and (d), Clayton copula rotated 90 degrees and Gumbel copula rotated 270 degrees capture strong dependence around the upper left area. It means that when one variable would take an extremely low value, then another variable tends to take an extremely high value. Note that the Gumbel copula rotated 270 degrees is also selected for the pair of the JPY with Europe index.

Almost all of the correlation parameters between each currency and each stock index are positive, from which we can guess that the most currencies are diversifier. However, the correlation parameters for the pairs of (i) the JPY with World, U.S. and Europe index, (ii) gold with U.S. Index, and (iii) Bitcoin with World and Pacific indices are negative. These results mean that the JPY, gold, and Bitcoin appreciate, when the stock index declines. Similar results can be re-confirmed by comparing the Kendall's τ. They are negative for all the pairs mentioned above. Thus, we can infer that the JPY, gold, and Bitcoin have hedge and /or safe haven currency status.

<Insert Table 2 and Figure 1>

Figure 2 displays the estimated dynamic conditional correlations. In the estimation, we choose multivariate t copula, because it fits most of the pairs. To examine their behavior more carefully, we divide sample periods into five sub-sample periods and calculate the average of the dynamic conditional correlation in Table 3. The average of the real value of the VIX is also calculated. The first sub-sample period is from January 2000 to June 2007, which is a tranquil period with lower VIX values before the global financial crisis. The second sub-sample covers the global financial crisis period from August 2007 to October 2009, and the third sub-sample covers the Greek sovereign crisis and the European sovereign crisis period from November 2010 to December 2012. We can see that the VIX increases sharply in these periods. The fourth sub-sample is a relatively tranquil period from January 2013 to May 2016, which is just before the Brexit. The last sub-sample is from Jun 2016 to December 2019, which includes the Brexit, the United States presidential election, and the trade dispute between the United States and China, namely, it covers the period when fear of populism and national particularism arises. However, the VIX is relatively lower in the last sub-sample period.

From Figure 2 and Table 3, we can see that there are some common patterns in the dynamic conditional correlations of the AUD, the CAD, the EUR, the SEK, and the GBP. First, almost all of the correlations with stock indices are positive. Second, the correlations are lower in the first sub-sample period, but they increase sharply during the global financial crisis and the European sovereign crisis period, and after the tranquil fourth period, they increase again slightly after the Brexit. However, there are also differences among these correlations. First, the correlations with regional stock indices are different in different currencies. For example, the correlation with the Pacific index is relatively higher in the AUD, and the correlation with the U.S. index are relatively higher in the CAD, while we can see little evidence that the correlations with Europe index are higher in the EUR, the SEK, and the GBP. Second, the EUR and the GBP had negative correlations with the U.S. index in the first sub-sample period, however, after the global financial crisis, they became positive, which means that the EUR and GBP had lost their hedge currency status against U.S. stock market. Therefore, we can infer that the AUD, the CAD, the EUR, the SEK, and the GBP are diversifier against the stock market because they are weakly and positively correlated with stock price indices on average.

The CNY has positive correlations over the sample periods on average, but the correlations are close to zero. This might be because a managed floating exchange rate regime has been adopted in China so that the changes of the CNH has been stable regardless of the movements in the stock markets. Therefore, we can infer that the CNY is a weak hedge because it is uncorrelated with stock price indices on average.

The CHF and gold share some similar properties. They are negatively correlated with the U.S. index except for the European sovereign crisis period. In addition, the CHF also has a negative correlation with the World index in the recent two sub-sample periods. These results mean that the CHF and gold are the strong hedges against the U.S. stock market because they are negatively correlated with the U.S. index on average. Moreover, they had strong safe haven currency status against the U.S. stock market in the global financial crisis period, but lost this status and became a diversifier during the European sovereign crisis.

The JPY has both hedge and safe-haven currency status because it has negative correlations with World, U.S., and Europe indices not only in the tranquil periods but also in the crisis periods. However, the correlation with the Pacific index is positive. This might be because the Pacific index includes Japanese stock prices itself, thus the JPY cannot be a hedge or a safe-haven currency against the Pacific stock markets.

The Bitcoin has a hedge status because it has negative correlations for most of the stock indices over the fourth and last sub-sample period. These results are consistent with the findings that Gumbel copula rotated 270 degrees and Clayton copula rotated 90 degrees are best fitted. However, because the sample period for Bitcoin does not include the financial turmoil events, we cannot infer whether Bitcoin has a safe-haven currency status.

<Insert Figure 2 and Table 3>

In the next step, we estimate the threshold model described by equation (12) to investigate whether market uncertainty measured by the VIX would have significant effects on the estimated dynamic conditional correlation, and whether there exists a threshold effect. As discussed above, if the VIX has statistically significant effects, but the threshold does not exist, it means that the degree of the role of the currency as a diversifier or hedge changes as the market uncertainty changes. If there exist thresholds, it can be interpreted as the evidence of “correlation breakdown”, namely, contagion. Otherwise, if the VIX does not have statistically significant effects and there are no threshold effects, it can be regarded as the interdependence when the correlations are high on average, or no-interdependence when the correlations are close to zero on average.

Table 4 shows the results. For the AUD and the CAD, the threshold effect does not exist, but the correlations with World, U.S., Europe, and Pacific (only for the CAD) indices are positively affected by the increase in the VIX. These results mean that the increase in market uncertainty would weaken their role as a diversifier because the correlations get closer to one. For the EUR, the SEK, and the CHF, there exists one threshold for the pairs with World and U.S. indices, and estimated coefficients β_{i_above} are positive and statistically significant, whereas estimated coefficients β_{i_below} are insignificant. Moreover, the CHF has one threshold and the estimated coefficient β_{i_above} is positive and statistically significant for the pair with Europe index. The estimated threshold values of $\ln vix_t$ are ranging from 3.2612 to 3.2715 corresponding to the real values of the VIX from 26.081 to 26.351, which exceed the third quantile in Table 1(a). These results mean that there exists a contagion effect between the EUR, the SEK, and the CHF foreign exchange markets and World and U.S. stock markets. As shown above, the correlation of the CHF and U.S. index is estimated to be negative except for the European sovereign crisis period, thus we infered that the CHF is a strong hedge against the U.S. stock market. Combining these results mean that the increase in market uncertainty weaken the role of the CHF as a hedge currency.

For the CNY, the GBP, and Bitcoin, all of the correlations are not affected by the change in the VIX. Because the CNY has little correlations with the stock price indices, these results mean that the degree of the CNH hedge currency status is not affected by the degree of market uncertainty. Similarly, we can say that the degrees of the GBP diversifier status and Bitcoin hedge haven status are not affected by market uncertainty.

For the JPY and gold, the threshold does not exist, but the correlations of the JPY with all stock indices, and correlations of gold with the World, Europe, and Pacific indices are affected negatively and statistically by the VIX. These results mean that the increase in market uncertainty would strengthen the role of their hedge and/or safe-haven currency status.

5.Conclusions

In this paper, we employ the Copula-DCC approach to investigate the safe-haven currency status of eight currencies as well as gold and Bitcoin. Since the copula approach can capture the tail dependence, it is suitable for the study on the periods when market uncertainty increases, and asset prices take extreme values. We follow the definitions of a diversifier, a hedge, and a safe haven proposed by Baur and Lucey (2010), and then classify the currencies into three categories.

The estimation results can be summarized as follows. First, the AUD, the CAD, the EUR, the SEK, and the GBP are diversifier against the stock markets, because they are weakly and positively correlated with stock price indices on average. Second, the CNH is a weak hedge because it is uncorrelated with stock price indices on average. Third, the CHF and gold are the strong hedges against the U.S. stock markets because they are negatively correlated with the U.S. stock index on average. Moreover, they had a role as a strong safe haven currency against the U.S. stock market during the global financial crisis but lost this status during the European sovereign crisis. Forth, the JPY has both hedge and safe haven currency status, because it has negative correlations with World, U.S., and Europe indices not only in the tranquil periods but also in the crisis periods. Lastly, the Bitcoin has hedge status.

In the next step, we estimate the threshold model to investigate whether market uncertainty measured by the VIX would have significant effects on the estimated dynamic conditional correlation, and whether there exists a threshold effect. This analysis is closely related to the study of contagion. The estimation results can be summarized as follows. First, the increase in market uncertainty would weaken the role of the AUD and the CAD as a diversifier because the correlations get closer to one as the VIX increases. Second, the contagion from World and U.S. stock markets would occur in the EUR, the SEK, and the CHF foreign exchange markets, because there exist threshold values, above which the VIX has statistically significant positive effects on the correlation. It means that the increase in market uncertainty weakens the role of the CHF as a hedge currency. Third, the movements in the stock market do not change the degrees of the roles as a hedge currency of the CNY and Bitcoin, and the role as a diversifier of the GBP, because the correlations are not affected by the VIX. Lastly, the roles of the JPY and gold as a hedge and safe haven currency increases as market uncertainty increases, because the VIX has statistically significant negative effects on the correlation.

There remain some topics for future research. First, in this paper, we use the USD as a *numeraire* currency, however, some papers show the importance of the USD as a safe-haven currency. Thus, there is a need to investigate the status of the USD. Second, in the analysis of contagion, we calculate the correlations from which we cannot infer causation, therefore, it might be useful to employ the causality in the quantile method to analyze the contagion between the foreign exchange markets and the stock markets by considering tail dependence. Third, in recent years, the Economic Policy Uncertainty (EPU) index proposed by Baker *et al*. (2016) are widely used as an indicator of market uncertainty. The EPU index is based on text-mining of a newspaper. It is calculated from the frequency of articles in 10 leading US newspapers that contain the following triple: (1)“economic” or “economy”; (2) “uncertain” or “uncertainty”; and one or more of “congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation” or “White House”. Because recent global economic risks are stemming from economic political uncertainty, it might be a useful indicator of market uncertainty.

References

Baur, D.G., and Lucey, B.M. 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45, 217–229.

Baker, S. R., Bloom, N. and Davis, S.J. 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593-1636.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D and Hagfors, L.I. 2017. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters* 20, 192–198.

Brunnermeier, M. K., Nagel, S. and Pedersen, L.H. 2008. Carry trade and currency crashes. *NBER Working Paper* No. 14473.

De Bock, R., and de Carvalho Filho, I. 2015. The behavior of currencies during risk-off episodes. *Journal of International Money and Finance,* 53, 218-234.

Engle, R. F. 2002. Dynamic conditional correlation: A simple class of multivariate GARCH Models. *Journal of Business and Economic Statistics* 20(3), 339–350.

Fatum, R. and Yamamoto, Y. 2016 Intra-safe haven currency behavior during the global financial crisis. *Journal of International Money and Finance* 66, 49–64.

Forbes, K. J., and Rigobon, R. 2002. No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance* 57(5), 2223–2261.

Fratzscher, M. 2009. What explains global exchange rate movements during the financial crisis? *Journal of International Money and Finance* 28, 1390-1407.

Habib, M. M. and Stracca, L. 2012. Getting beyond carry trade: What makes a safe haven currency? *Journal of International Economics*, 87(1), 50-64.

Hansen, B.E., 2000. Sample splitting and threshold estimation. *Econometrica* 68, 575–603.

Jondeau, E., and Rockinger, M. 2006. The Copula-GARCH model of conditional dependencies: An international stock market application. *Journal of International Money and Finance* 25, 827–853.

Kaul, A., and Sapp, S., 2006. Y2K fears and safe haven trading of the U.S. dollar. *Journal of International Money and Finance* 25, 760–779.

Kim, J-M. and Jung, H. 2016. Linear time-varing regression with Copula-DCC-GARCH models for volatility. *Economic Letters* 145, 262-265.

Masujima, Y. 2017. Safe haven currency and market uncertainty: Yen, renminbi, dollar, and alternatives, RIETI Discussion Paper Series 17-E-048.

Patton, A. J. 2006. Modelling asymmetric exchange rate dependence. *International Economic Review* 47 (2), 527–556.

Peng, Y., and Ng, W. 2011. Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. *Annals of Finance* 8(1), 1–26.

Ranaldo, A. and Söderlind, P. 2010. Safe haven currencies. *Review of Finance* 14, 385–407.

Ratner, M. , Chiu, C. , 2013. Hedging stock sector risk with credit default swaps. *International Review of Financial Analysis* 30, 18–25.

Rodriguez, J. C. 2007. Measuring financial contagion: A copula approach. *Journal of Empirical Finance* 14(3), 401–423.

Table 1(a) Descriptive statistics

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC	WORLD	U.S.	EUROPE	PACIFIC	VIX(level)
Observations	5217	5217	3769	5217	5217	5217	5217	5217	5217	1741	5217	5217	5217	5217	5217
Mean	0.00004	0.00004	0.00005	0.00004	0.00001	0.00001	0.00012	-0.00002	0.00037	0.00391	0.00014	0.00021	0.00012	0.00009	19.48799
3rd Quantile	0.00429	0.00303	0.00062	0.00336	0.00324	0.00429	0.00355	0.00321	0.00558	0.02196	0.00484	0.00545	0.00658	0.00634	22.92000
Median	0.00021	0.00000	0.00000	0.00004	0.00000	0.00000	0.00000	0.00000	0.00015	0.00195	0.00053	0.00028	0.00032	0.00032	17.30000
1st Quantile	-0.00391	-0.00292	-0.00049	-0.00343	-0.00336	-0.00412	-0.00349	-0.00321	-0.00444	-0.01550	-0.00412	-0.00435	-0.00580	-0.00579	13.48000
Max	0.08311	0.03951	0.01999	0.03482	0.03886	0.05797	0.18698	0.03135	0.07106	0.68336	0.09523	0.11675	0.11291	0.10331	80.86000
Min	-0.08326	-0.03345	-0.01819	-0.02636	-0.05037	-0.04147	-0.08689	-0.08058	-0.09663	-0.23371	-0.07063	-0.09075	-0.09677	-0.08773	9.14000
Standard Deviation	0.00791	0.00549	0.00162	0.00612	0.00618	0.00749	0.00698	0.00578	0.01062	0.05157	0.00976	0.01169	0.01309	0.01177	8.45885

(1) The exchange rates, prices of gold and Bitcoin and stock price indices are in the first difference in the logarithm. The VIX is in the actual value.

Table1 (b) Unconditional correlations

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC	WORLD	U.S.	EUROPE	PACIFIC
AUD	1													
CAD	0.6345	1												
CNY	0.1439	0.0992	1											
EUR	0.5555	0.4555	0.1237	1										
JPY	0.0102	-0.012	0.0486	0.2538	1									
SEK	0.5975	0.5069	0.1318	0.8113	0.1366	1								
CHF	0.3619	0.2924	0.0864	0.7397	0.369	0.5867	1							
GBP	0.5067	0.4364	0.1437	0.6249	0.1299	0.5727	0.4675	1						
GOLD	0.2235	0.203	0.1505	0.2774	0.2025	0.2391	0.297	0.2094	1					
BTC	-0.0059	-0.0139	-0.0331	0.0092	0.0264	0.0064	0.0525	0.0042	0.0128	1				
WORLD	0.5318	0.4952	0.1155	0.2447	-0.2285	0.3959	0.0438	0.291	0.0618	-0.0089	1			
USA	0.4394	0.4175	0.0572	0.1162	-0.2997	0.2779	-0.0764	0.174	-0.046	-0.0081	0.8951	1		
EUROPE	0.4692	0.445	0.1446	0.3398	-0.1485	0.4449	0.1683	0.3539	0.1206	-0.0001	0.8298	0.5433	1	
PACIFIC	0.2776	0.1806	0.13	0.1663	0.1538	0.1754	0.1311	0.1812	0.1862	-0.0242	0.3971	0.1113	0.3507	1

Table 2 Selections of copula

WORLD

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Copula	Survival Gumbel	t	Gaussian	t	t	t	t	t	t	Gumbel Rotated 270 degrees
Correlation	1.43	0.42	0.12	0.22	-0.16	0.33	0.06	0.23	0.08	-1.01
Kendall's tau	0.3	0.28	0.08	0.14	-0.1	0.21	0.04	0.15	0.05	-0.01
Upper TD	0	0.19	0	0.15	0.04	0.18	0.08	0.09	0.08	0
Lower TD	0.38	0.19	0	0.15	0.04	0.18	0.08	0.09	0.08	0

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Copula	t	t	Clayton	t	t	t	t	t	t	Clayton
Correlation	0.33	0.35	0.06	0.07	-0.26	0.2	-0.08	0.11	-0.04	0.06
Kendall's tau	0.22	0.23	0.03	0.05	-0.17	0.13	-0.05	0.07	-0.03	0.03
Upper TD	0.21	0.16	0	0.11	0.02	0.14	0.05	0.05	0.04	0
Lower TD	0.21	0.16	0	0.11	0.02	0.14	0.05	0.05	0.04	0

Europe

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Copula	Survival Gumbel	t	Gaussian	t	Gumbel Rotated 270 degrees	t	t	t	t	Clayton
Correlation	1.37	0.38	0.16	0.32	-1.09	0.4	0.18	0.32	0.14	0.03
Kendall's tau	0.27	0.25	0.1	0.21	-0.08	0.26	0.12	0.21	0.09	0.02
Upper TD	0	0.15	0	0.16	0	0.19	0.08	0.1	0.11	0
Lower TD	0.34	0.15	0	0.16	0	0.19	0.08	0.1	0.11	0

Pacific

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Copula	t	t	Gaussian	t	t	t	t	t	t	Clayton Rotated 90 degrees
Correlation	0.29	0.17	0.14	0.17	0.21	0.19	0.16	0.17	0.2	-0.03
Kendall's tau	0.19	0.11	0.09	0.11	0.14	0.12	0.1	0.11	0.13	-0.02
Upper TD	0.11	0.04	0	0.05	0.11	0.05	0.03	0.02	0.06	0
Lower TD	0.11	0.04	0	0.05	0.11	0.05	0.03	0.02	0.06	0

Table 3. Estimation results of copula-DCC model

	AUD				CAD				CNY				EUR			
	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC
2000.Jan-2007.June	0.282	0.149	0.332	0.279	0.246	0.146	0.276	0.193	0.059	0.002	0.097	0.102	0.106	-0.059	0.287	0.176
2007.Aug-2009.Oct	0.582	0.482	0.528	0.301	0.526	0.442	0.500	0.149	0.016	-0.008	0.038	0.023	0.296	0.151	0.388	0.207
2010.Nov-2012.Dec	0.697	0.616	0.605	0.404	0.674	0.640	0.574	0.248	0.140	0.077	0.147	0.160	0.554	0.425	0.578	0.280
2013.Jan-2016.May	0.370	0.285	0.301	0.271	0.376	0.313	0.317	0.154	0.071	0.004	0.104	0.136	0.105	0.020	0.208	0.084
2016.Jun-2019.Dec	0.416	0.321	0.348	0.286	0.404	0.329	0.335	0.187	0.168	0.061	0.232	0.174	0.166	0.036	0.294	0.189
	JPY				SEK				CHF				GBP			
	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC
2000.Jan-2007.June	0.060	-0.064	0.074	0.329	0.213	0.054	0.366	0.208	0.026	-0.130	0.210	0.160	0.118	-0.030	0.266	0.166
2007.Aug-2009.Oct	-0.432	-0.492	-0.288	0.076	0.431	0.294	0.494	0.193	0.036	-0.101	0.186	0.142	0.329	0.201	0.408	0.185
2010.Nov-2012.Dec	-0.114	-0.200	-0.088	0.171	0.607	0.498	0.604	0.282	0.352	0.220	0.398	0.252	0.494	0.388	0.499	0.254
2013.Jan-2016.May	-0.306	-0.371	-0.191	0.055	0.178	0.094	0.265	0.106	-0.022	-0.098	0.088	0.085	0.199	0.116	0.253	0.122
2016.Jun-2019.Dec	-0.252	-0.324	-0.151	0.171	0.293	0.172	0.370	0.197	-0.006	-0.108	0.129	0.175	0.211	0.105	0.314	0.148
	GOLD				BTC				VIX							
	WORLD	U.S.	EUROPE	PACIFIC	WORLD	U.S.	EUROPE	PACIFIC								
2000.Jan-2007.June	0.082	-0.044	0.158	0.206	-	-	-	-	19.444							
2007.Aug-2009.Oct	0.084	-0.040	0.167	0.203	-	-	-	-	31.307							
2010.Nov-2012.Dec	0.252	0.125	0.290	0.226	-	-	-	-	21.547							
2013.Jan-2016.May	0.047	-0.039	0.075	0.161	-0.024	-0.028	-0.002	-0.025	15.398							
2016.Jun-2019.Dec	0.022	-0.080	0.096	0.200	0.011	-0.003	0.032	-0.008	14.299							

Table 4. Estimation Results of threshold model

World

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Thereshold Analysis										
Number of Threshold	0	0	0	1	0	1	1	0	0	0
Threshold	-	-	-	3.2612	-	3.2612	3.2612	-	-	-
l_vix	0.0019***	0.0026***	-0.0003	-	-0.0023***	-	-	0.0002	-0.0025***	-0.0003
	(0.0006)	(0.0006)	(0.0007)	-	(0.0007)	-	-	(0.0007)	(0.0008)	(0.0011)
l_vix(below)	-	-	-	0.0003	-	0.0017	-0.0005	-	-	-
	-	-	-	(0.0011)	-	(0.0011)	(0.0011)	-	-	-
l_vix(above)	-	-	-	0.0130***	-	0.0123***	0.0152***	-	-	-
	-	-	-	(0.0029)	-	(0.0028)	(0.0029)	-	-	-
constant	-0.0041**	-0.0056***	0.0019	-	0.0060***	-	-	0.0003	0.0079***	0.0007
	(0.0018)	(0.0018)	(0.0021)	-	(0.0021)	-	-	(0.0020)	(0.0025)	(0.0029)
constant(below)	-	-	-	0.0002	-	-0.0032	0.0020	-	-	-
	-	-	-	(0.0031)	-	(0.0029)	(0.0031)	-	-	-
constant(above)	-	-	-	-0.0464***	-	-0.0424***	-0.0549***	-	-	-
	-	-	-	(0.0101)	-	(0.0097)	(0.0102)	-	-	-
dcc(-1)	0.9963***	0.9953***	0.9883***	0.9963***	0.9962***	0.9956***	0.9960***	0.9958***	0.9915***	0.9766***
	(0.0011)	(0.0012)	(0.0025)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0013)	(0.0017)	(0.0052)

U.S.

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Thereshold Analysis										
Number of Threshold	0	0	0	1	0	1	1	0	0	0
Threshold	-	-	-	3.2623	-	3.2623	3.2612	-	-	-
l_vix	0.0027***	0.0029***	0.0006	-	-0.0014**	-	-	0.0010	-0.0008	0.0001
	(0.0007)	(0.0007)	(0.0007)	-	(0.0007)	-	-	(0.0007)	(0.0006)	(0.0012)
l_vix(below)	-	-	-	0.0013	-	0.0026**	0.0002	-	-	-
	-	-	-	(0.0011)	-	(0.0011)	(0.0011)	-	-	-
l_vix(above)	-	-	-	0.0136***	-	0.0130***	0.0145***	-	-	-
	-	-	-	(0.0030)	-	(0.0029)	(0.0029)	-	-	-
constant	-0.0064***	-0.0069***	-0.0012	-	0.0031	-	-	-0.0024	0.0021	-0.0007
	(0.0019)	(0.0019)	(0.0021)	-	(0.0021)	-	-	(0.0021)	(0.0016)	(0.0031)
constant(below)	-	-	-	-0.0031	-	-0.0063**	-0.0008	-	-	-
	-	-	-	(0.0031)	-	(0.0031)	(0.0031)	-	-	-
constant(above)	-	-	-	-0.0483***	-	-0.0447***	-0.0524***	-	-	-
	-	-	-	(0.0105)	-	(0.0102)	(0.0103)	-	-	-
dcc(-1)	0.9955***	0.9953***	0.9874***	0.9960***	0.9956***	0.9951***	0.9956***	0.9952***	0.9930***	0.9714***
	(0.0012)	(0.0012)	(0.0026)	(0.0011)	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0016)	(0.0057)

Europe

	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Thereshold Analysis										
Number of Threshold	0	0	0	0	0	0	1	0	0	0
Threshold	-	-	-	-	-	-	3.2715	-	-	-
l_vix	0.0017***	0.0025***	-0.0007	-0.0007	-0.0022**	0.0003	-	-0.0003	-0.0032***	0.0002
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	-	(0.0006)	(0.0011)	(0.0011)
l_vix(below)	-	-	-	-	-	-	-0.0006	-	-	-
	-	-	-	-	-	-	(0.0010)	-	-	-
l_vix(above)	-	-	-	-	-	-	0.0103***	-	-	-
	-	-	-	-	-	-	(0.0028)	-	-	-
constant	-0.0029***	-0.0047***	0.0035*	0.0034*	0.0059***	0.0012	-	0.0028	0.0110***	-0.0002
	(0.0018)	(0.0018)	(0.0020)	(0.0019)	(0.0021)	(0.0018)	-	(0.0019)	(0.0034)	(0.0029)
constant(below)	-	-	-	-	-	-	0.0030	-	-	-
	-	-	-	-	-	-	(0.0029)	-	-	-
constant(above)	-	-	-	-	-	-	-0.0370***	-	-	-
	-	-	-	-	-	-	(0.0098)	-	-	-
dcc(-1)	0.9943***	0.9927***	0.9889***	0.9960***	0.9944***	0.9949***	0.9949***	0.9941***	0.9879***	0.9707***
	(0.0014)	(0.0015)	(0.0024)	(0.0013)	(0.0014)	(0.0014)	(0.0013)	(0.0015)	(0.0021)	(0.0058)

Pacific

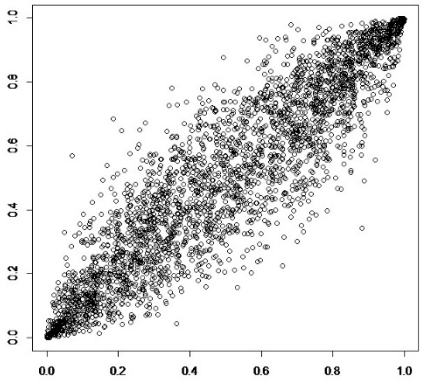
	AUD	CAD	CNY	EUR	JPY	SEK	CHF	GBP	GOLD	BTC
Thereshold Analysis										
Number of Threshold	0	0	0	0	0	0	0	0	0	0
Threshold	-	-	-	-	-	-	-	-	-	-
l_vix	0.0001	0.0011*	-0.0007	-0.0001	-0.0025**	-0.0001	-0.0008	0.0001	-0.0019***	-0.0011
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0011)
l_vix(below)	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
l_vix(above)	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
constant	0.0032*	0.0006	0.0039*	0.0026	0.0086***	0.0029	0.0047**	0.0022	0.0103***	0.0023
	(0.0018)	(0.0018)	(0.0021)	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0018)	(0.0022)	(0.0030)
constant(below)	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
constant(above)	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-
dcc(-1)	0.9882***	0.9799***	0.9844***	0.9878***	0.9928***	0.9863***	0.9864***	0.9851***	0.9759***	0.9551***
	(0.0022)	(0.0028)	(0.0029)	(0.0022)	(0.0015)	(0.0023)	(0.0023)	(0.0024)	(0.0030)	(0.0071)

(1) Standard errors are in parentheses.

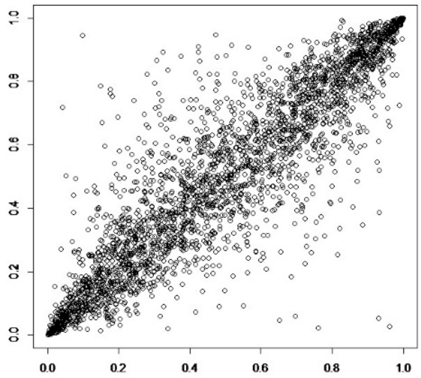
(2) The asterisks ***, **, * denote significance at the 1, 5, 10 % level, respectively.

Figure 1. Examples of Copulas

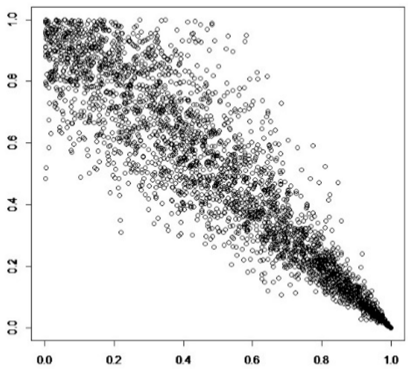
(a) Normal copula



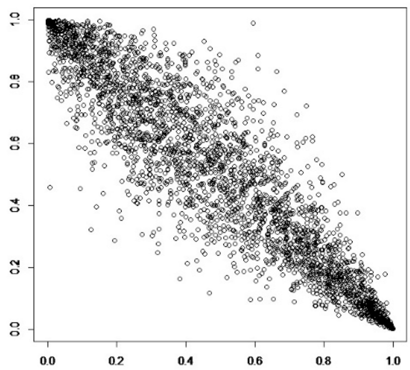
(b)Student-t copula



(c) Clayton copula rotated 90 degrees

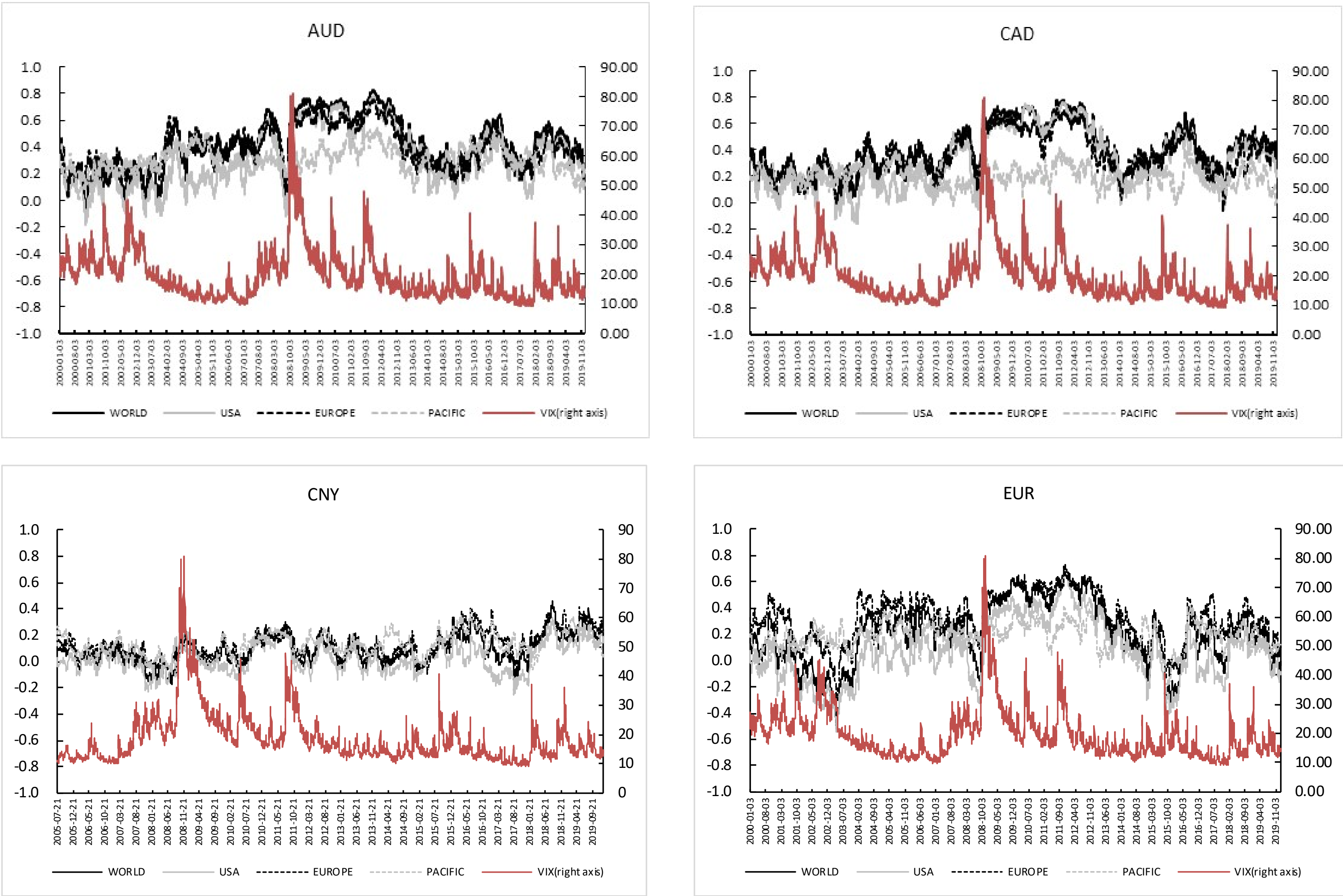


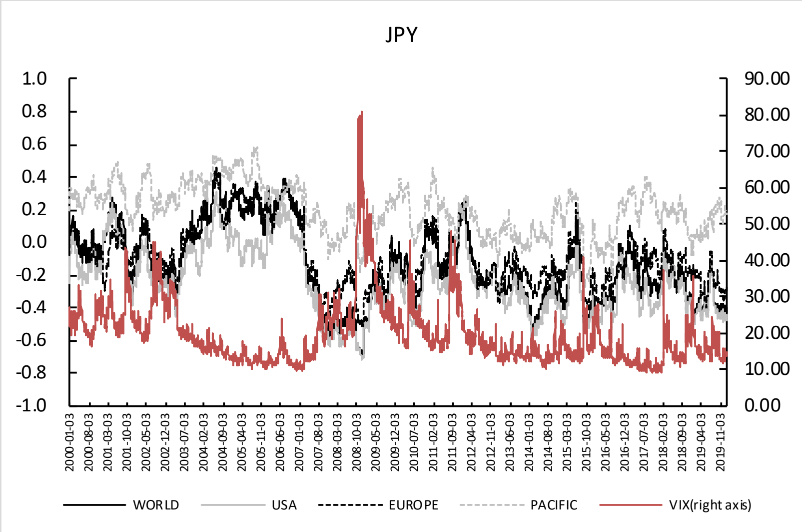
(d) Gumbel copula rotated 90 degrees

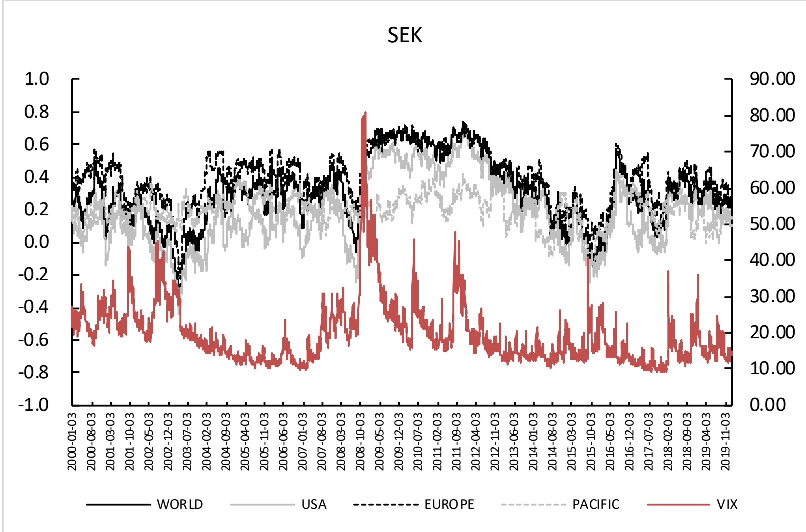


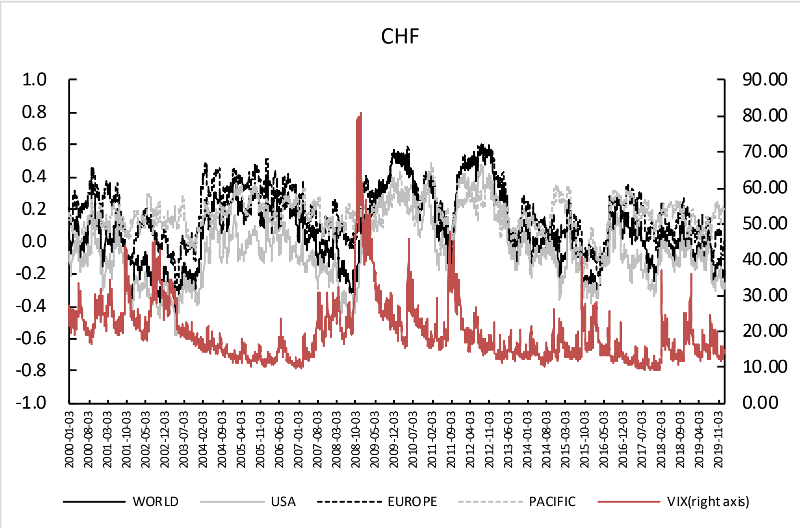
(1) These figures are plotted for the case of Kendall's τ =0.75.

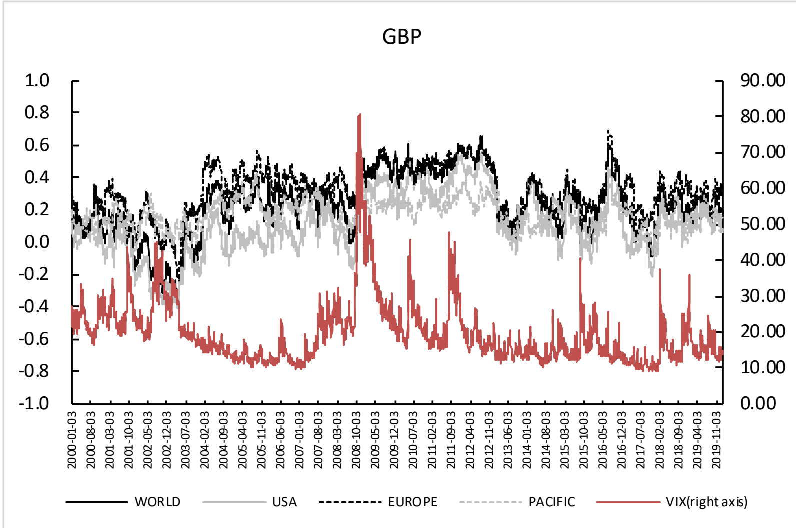
Figure 2. Estimation results of copula-DCC model

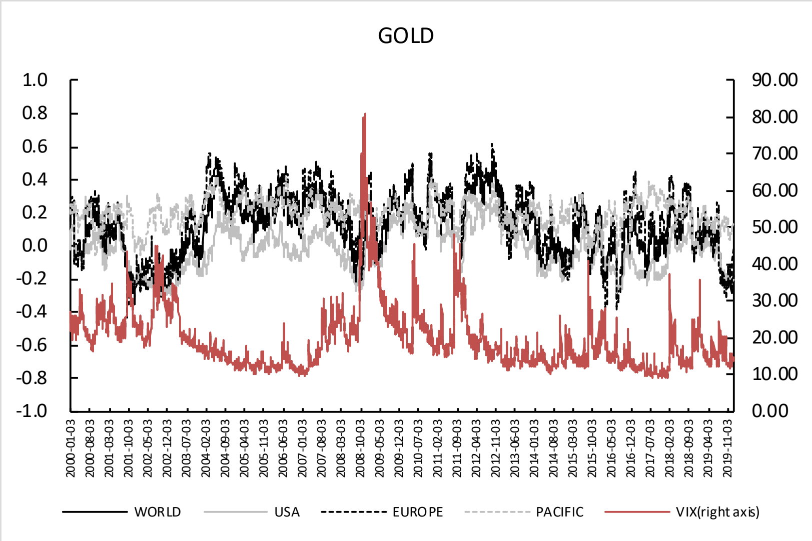


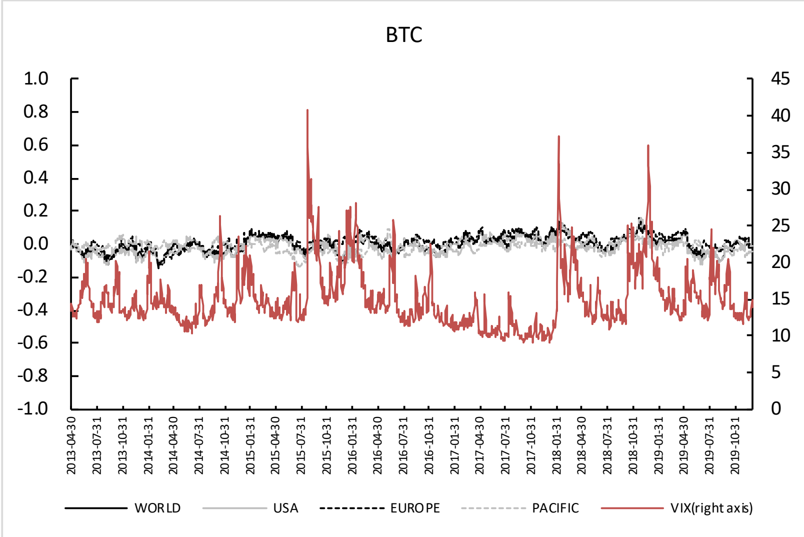

JPY
WORLD
USA
EUROPE
PACIFIC
VIX(right axis)


SEK
WORLD
USA
EUROPE
PACIFIC
VIX


CHF
WORLD
USA
EUROPE
PACIFIC
VIX(right axis)


GBP
WORLD
USA
EUROPE
PACIFIC
VIX(right axis)


GOLD
WORLD
USA
EUROPE
PACIFIC
VIX(right axis)


BTC
WORLD
USA
EUROPE
PACIFIC
VIX(right axis)