# Safe haven currencies: A dependence-switching copula approach

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February 2024

**Abstract**

This paper investigates the extreme comovement between exchange rates and market risk to identify safe haven currencies. Specifically, we employ a dependence-switching copula model and tail dependence between currencies and global market risk to measure the strength of safe haven currencies directly. We focus on the currencies, including the US dollar, the Japanese yen, the Swiss franc, the euro, and the British pound. Using daily data spanning from January 1999 to December 2022, our analysis reveals compelling evidence that the US dollar serves as a safe haven or refuge during periods of heightened global risk aversion. Moreover, the safe haven attributes of the yen remain prominent even in the presence of the US dollar's safe haven behaviour. Additionally, the Swiss franc exhibits safe haven characteristics, albeit less pronounced than the US dollar. Conversely, the euro and the pound demonstrate the weakest safe haven characteristics among the currencies studied.

Keywords: Safe haven currency; dependence-switching copula; VIX.

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# 1 Introduction

A safe haven currency refers to a currency that investors tend to flock to during times of economic or geopolitical uncertainty. These currencies are perceived as relatively stable and reliable stores of value, and investors seek them as a way to protect their investments from volatility or the risk of other assets. In particular, a safe haven currency tends to maintain its value or even appreciate in the wake of a crisis when the market risk is high. Recent global events such as the COVID-19 pandemic, the 2022 Russian invasion of Ukraine, and the European sovereign debt crisis have enhanced the world market risk. In times of such market stress or turmoil with enhanced market risk, detecting safe haven currencies is essential for investors, policymakers, and market participants seeking to navigate volatile market conditions, manage risk, and preserve capital in an uncertain economic environment. In this paper, we examine potential safe haven currencies and detect the relative degree to which they exhibit safe haven properties via their relationship to amplified global risk.

We consider a list of the most promising safe haven currencies documented in the literature: The United States (US) dollar (USD), the Japanese yen (JPY), the Swiss franc (CHF), the euro (EUR), and the British pound (GBP). The seigniorage of the USD can partially justify its status as a safe haven (Prasad, 2015). It serves as a crucial vehicle currency for clearing international payments and invoicing trade flows. Some countries have even outright adopted the USD as their own or linked their currencies at a fixed exchange rate (Calvo, 2002). The USD largely appreciated during the global financial crisis of 2007–2008. McCauley and McGuire (2009) attribute the USD's appreciation during this crisis mainly to dollar shortages resulting from a surge in dollar funding costs, flights to US Treasury bills, and the write-down of USD-denominated assets that led to overhedged books.

As for the yen, there is a consensus that it is a safe haven. One possible explanation is that foreign ownership of Japanese debt is very low, resulting in less selling pressure during times of crisis (Hoque, 2012). Other contributing factors include a chronic trade surplus and deflation. It is worth noting that recent actions by the Bank of Japan to increase its balance sheet could potentially undermine the yen's status as a safe haven.

Regarding the CHF, the traditional view is that it provides safe haven or hedging benefits on average (Kugler and Weder, 2004). However, the actual performance of the CHF is mixed (Grisse and Nitschka, 2015; Hossfeld and MacDonald, 2015; Fatum and Yamamoto, 2016). Additionally, Coudert et al. (2014) argue that the franc's long-run appreciation is more of a continuous trend than a specific reaction to global financial turmoil. Switzerland's perceived relative stability can be attributed to its intrinsic low-risk profile, including the protection of individual financial rights and adherence to a foreign policy of neutrality.

In addition to the currencies mentioned above, the euro and the pound sterling are often included in studies related to safe haven currencies (Ranaldo and Söderlind, 2010; Coudert et al., 2014; Hossfeld and MacDonald, 2015; Fatum and Yamamoto, 2016; Tachibana, 2018; Wong and Fong, 2018). According to data provided by the Bank for International Settlements (BIS), the euro and the pound rank as the second and fourth most traded currencies, respectively. This fact partly motivates their inclusion in studies examining currencies that serve as safe harbours of value. Other considerations for their incorporation include their international status, reputation, and underlying fundamentals (De Santis, 2012; Habib and Stracca, 2012; Coudert et al., 2014; Hossfeld and MacDonald, 2015).

Since safe haven currencies are those that maintain or even appreciate in value during market turmoil or crisis, detecting them requires measuring global market risk. Most research relies on the Chicago Board Options Exchange (CBOE) Volatility Index or the VIX index to gauge market risk (Ranaldo and Söderlind, 2010; Coudert et al., 2014; De Bock and de Carvalho Filho, 2015;

Fatum and Yamamoto, 2016). Indeed, prior studies have established that the VIX is sufficient to measure market-wide distress (Collin-Dufresn et al., 2001; Pan and Singleton, 2008; Gyntelberg and Schrimpf, 2011; Rey, 2015). For additional details on measuring market risk via the VIX, see Carr and Wu (2006), Whaley (2009), Gonzalez-Perez (2015), and Martin (2017).

In the literature, VIX has been shown as a proper proxy of global market risk. Habib and Stracca (2012) use a panel approach and the VIX to measure global risk to determine which fundamentals are essential to safe haven behaviour. Although they advocate using alternative risk estimates to check the robustness of the results, they find that the results are similar regardless. Similarly, influenced by Habib and Stracca's (2012) procedure, Fatum and Yamamoto's (2016) primary market uncertain benchmark is also the VIX. The consensus from both studies is that implementing the alternatives to the VIX in their models does not substantially alter their findings. Additionally, the correlation between the VIX and the competing measures is relatively high and positive. Fatum and Yamamoto (2016) also establish the causal relationship to be from the VIX to the exchange rate. Wong and Fong (2018) acknowledge the use of the VIX outside of the US equity markets to gauge global risk, citing studies such as Collin-Dufresn et al. (2001), Pan and Singleton (2008), and Rey (2015). Nevertheless, they construct a risk aversion index using the first principal component from nine stock market volatility indexes. Similar to Habib and Stracca (2012) and Fatum and Yamamoto (2016), there is a high positive correlation between these indexes. Moreover, their results are consistent with studies mainly using the VIX (for example, Grisse and Nitschka (2015)).

In this paper, we follow the literature and use the VIX as a proxy for global market risk. When the VIX is high, it signals heightened global risk aversion, precisely when a safe haven currency is most in demand.Therefore, when the VIX is high, we expect an appreciation of the suspected safe haven currency. In addition to the VIX, we also use volatility indexes based on the European and

Swiss markets as robustness checks, yielding similar results.

In the literature, the identification and analysis of safe haven currencies rely on regression analysis using the sign/magnitude of regression coefficients on market risk, such as VIX, see Ranaldo and Söderlind (2010), Coudert et al. (2014), Hossfeld and MacDonald (2015), Fatum and Yamamoto (2016), and Wong and Fong (2018). For instance, Ranaldo and Söderlind (2010) and Coudert et al. (2014) use risk factor models and a smooth transition regression (STR) model, respectively, which lean upon population orthogonality conditions for consistency. Lee (2017) employs Markov regime-switching vector autoregressive (MS-VAR) models to assess the negative relationship between safe haven currencies and risky assets. Reboredo (2013) uses tail dependence and the copula method to assess the role of gold as a safe haven or hedge against the USD. Tachibana (2018) adopts a copula-based approach to characterize the relationship between stock returns and exchange rate changes to identify safe haven and hedge currencies.

We investigate safe haven currencies based on the tail dependence between the currency and the VIX, as a safe haven currency implies a positive right tail correlation or dependence between the currency value and the market risk proxy, the VIX. When the VIX (also known as "the fear index") spikes, demand for safe assets/currencies increases, resulting in a significant positive return for the safe haven currency. Therefore, we gauge the extent to which a currency serves as a safe haven by estimating the tail correlations between the currency and the VIX. Specifically, we evaluate the tail dependence between an exchange rate and the VIX by employing a dependence-switching copula model (Wang et al., 2013, 2018).

The dependence-switching copula model allows for both positive and negative dependence between two variables, which is critical in the foreign exchange (FX) market, where extreme outcomes are possible on both ends of the spectrum. In the positive dependence regime, the right/upper tail dependence between the currency value and VIX indicates the safe haven status of the currency, while in the negative dependence regime, significant dependence between the left tail of the currency value (depreciation of the currency) with the right tail of VIX (high risk) suggests the currency is not a safe haven. Our approach to studying safe haven currencies using tail dependence allows us to measure the comovement of exchange rates under extreme market conditions with heightened volatility. Thus, this approach provides insights where other methodologies, such as regressions, may be lacking. Furthermore, our copula approach captures the nonlinear dependence and dependence structure between currencies and the VIX, and the estimation of tail dependence does not require a predefined threshold.

Our copula approach is also different from that of Reboredo (2013) and Tachibana (2018) in several ways. First, we use a dependence-switching copula that is more flexible and allows for both positive and negative tail dependence, whereas their copula models can only capture positive dependence. Second, we model the tail dependence between currencies and the VIX to identify the safe haven currencies, while Reboredo (2013) and Tachibana (2018) examine the tail correlation between the USD–gold and currency–stock returns, respectively.

Using the dependence-switching copula model and estimating the tail dependence between exchange rates and VIX, we find that the USD is a significant safe haven currency. Further, we find that the JPY also serves as a safe haven currency, which is not dominated by the appreciation of the USD in times of heightened global risk aversion. However, while the euro and the pound exhibit safe haven characteristics, these effects are overshadowed by the similar behavior of the USD. The CHF demonstrates safe haven features to a lesser extent than the USD and the JPY, but more so than the euro and the pound. Our results are generally consistent with previous studies by Ranaldo and Söderlind (2010), Hossfeld and MacDonald (2015), Fatum and Yamamoto (2016), and

Wong and Fong (2018). However, our research advances the literature by offering a more direct method for identifying safe haven currencies and providing a deeper understanding of safe haven currencies. For instance, while Wong and Fong's (2018) study offers valuable insights, it does not quantify the degree or relative strength of safe haven characteristics across different currencies to the extent that our research does.

In summary, we contribute to the literature as follows: First, the dependence-switching copula model is flexible and particularly useful in assessing the relative strength of the safe haven currencies. By considering tail dependence, we can directly gauge how currency values fluctuate during extreme market conditions, especially during periods of high risk, which is closely tied to the concept of safe haven currencies. Unlike the linear regression approach commonly used in the literature, our model captures the safe haven property precisely when it is most relevant. Second, the model accommodates both positive and negative dependence between exchange rates and market risk and the switches between them. This is useful as the positive and negative dependence corresponds to the safe haven status of the denominator and the numerator currencies when the market risk is heightened, respectively. Thus, we do not impose directional restrictions on their dependence, and hence do not restrict the safe haven behaviour of any currencies. Finally, our flexible methodology yields new insights. We find that the USD, the JPY, and the CHF exhibit safe haven characteristics at varying levels. The USD emerges as a strong safe haven relative to all other currencies except for the JPY, which stands out as the strongest safe haven currency. The CHF also demonstrates safe haven attributes, albeit weaker than the USD, while the GBP and the EUR show the weakest safe haven characteristics.

The remainder of the paper is structured as follows. Section 2 provides the details of the joint model, the dependence measures, the marginal models, and the estimation procedure. Section 3 describes the data and provides the summary statistics. Our empirical results are presented in Section 4. Section 5 concludes.

# 2 Models and estimation

## 2.1 Joint model: the dependence switching copula model

Copulas ($C(\cdot, ..., \cdot)$) are functions that combine univariate marginal distributions ($F_1(\cdot), ..., F_N(\cdot)$) to construct their respective joint distribution ($F(\cdot, ..., \cdot)$) (Sklar, 1959). To measure the dependence structure between the market risk and currencies, we adopt the dependence-switching copula model of Wang et al. (2018). Let $u_{1,t}$ and $u_{2,t}$ be the probability integral transforms that pertain to the volatility index, the VIX and the exchange rate percentage changes, with $C(\cdot, \cdot)$ representing the copula function that describes the dependence structure between the two series. Consider the following state-varying copula:

$$C\big(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_1^C, \boldsymbol{\theta}_0^C | S_t\big) = \begin{cases} C_1\big(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_1^C\big), & \text{if } S_t = 1 \\ C_0\big(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_0^C\big), & \text{if } S_t = 0 \end{cases}, \tag{1}$$

where $S_t$ is an unobserved state variable representing either a positive ($S_t = 1$) or a negative ($S_t = 0$) dependence state.

In the above equation, $C_1\big(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_1^C\big)$ and $C_0\big(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_0^C\big)$ are two mixed copulas corresponding to the positive and negative dependence states or regimes, with $\boldsymbol{\theta}_1^C$ and $\boldsymbol{\theta}_0^C$ denoting the corresponding parameter vectors for each state, respectively. The state variable $S_t$ follows a Markov chain with a transition matrix $\mathbf{\Pi}$, i.e.,

$$\mathbf{\Pi} = \begin{bmatrix} \Pi_{00} & 1-\Pi_{00} \\ 1-\Pi_{11} & \Pi_{11} \end{bmatrix}, \tag{2}$$

where $\Pi_{00} = \Pr(S_t = 0|S_{t-1} = 0)$ and $\Pi_{11} = \Pr(S_t = 1|S_{t-1} = 1)$. Hence, $\Pi_{00}$ is the probability of two successive negative dependence states, with $1 - \Pi_{00}$ quantifying the chance of transitioning out of the negative dependence state (regime). A similar interpretation will hold for $\Pi_{11}$ and $1-\Pi_{11}$.

Since the mixture of two Archimedean copulae is also an Archimedean copula (see Nelsen 2006), we mix a Clayton copula ($C^C(\cdot,\cdot)$) with a survival Clayton copula ($C^{SC}(\cdot,\cdot)$) to allow for both left and right tail dependence:

$$C_1(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_1^C) = w_1 \times C^C(u_{1,t}, u_{2,t}; \chi_1) + (1-w_1) \times C^{SC}(u_{1,t}, u_{2,t}; \chi_2), \tag{3}$$

$$C_0(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_0^C) = w_2 \times C^C(1-u_{1,t}, u_{2,t}; \chi_3) + (1-w_2) \times C^{SC}(1-u_{1,t}, u_{2,t}; \chi_4), \tag{4}$$

where $\boldsymbol{\theta}_1^C = (\chi_1, \chi_2, w_1)'$, $\boldsymbol{\theta}_0^C = (\chi_3, \chi_4, w_2)'$, and $\chi_k \in (0, \infty)$ $(k = 1, 2, 3, 4)$ are copula parameters, and $w_1$ and $w_2$ are the weights for the corresponding copulas. The bivariate Clayton copula and the survival Clayton copula are given by $C^C(u_1, u_2; \chi_k) = (u_1^{-\chi_k} + u_2^{-\chi_k} - 1)^{-\frac{1}{\chi_k}}$ and $C^{SC}(u_1, u_2; \chi_k) = u_1 + u_2 - 1 + C^C(1-u_1, 1-u_2; \chi_k)$. The advantage of this joint model is that it allows for both positive and negative dependence states or regimes with the capacity to transition between them. For a more complete discussion and properties of copulas, please refer to Nelsen (2007) and Joe (1997).

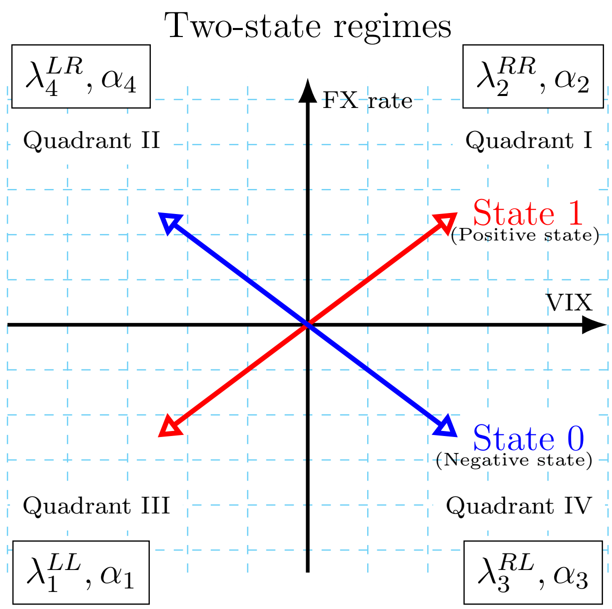
## 2.2 Dependence measures

We can assess dependence using a set of measures derived from the joint model, including the correlation coefficient and tail dependence. Common measures of dependence include the Pearson correlation, Spearman's $\rho$ and Kendall's $\tau$. Rank correlations such as Spearman's $\rho$ and Kendall's $\tau$ are often preferred over the Pearson correlation coefficient because they can capture nonlinearities, are invariant under increasing transformations, and depend only on the joint distribution (Joe, 2014; McNeil et al., 2015). Additionally, Kendall's $\tau$, which represents the difference between the probability of concordance and discordance for two random variables, can be estimated through the copula parameter ($\alpha_k$) as $\tau_k(X_1, X_2) = \frac{\alpha_k}{2+\alpha_k}$. The correlation coefficient ($\rho_k$) can then be computed using Kendall's $\tau$, i.e., $\rho_k(X_1, X_2) = \sin\left(\frac{\pi}{2} \times \tau_k(X_1, X_2)\right)$. From a risk management perspective, in addition to the commonly used dependence measures mentioned above, tail dependence is particularly important in decision-making during extreme market condition(Embrechts et al., 2002).

To capture the dependence at extremes, we use tail dependence measures. By definition, the upper (lower) or right (left) tail dependence measure quantifies the probability of observing a high (low) $U_1$, given that $U_2$ is high (low). The Clayton copula only exhibits lower tail dependence, while the survival Clayton only has upper tail dependence. The mixture of the two copulas, in combination with the state-switching aspect, results in four different configurations of tail dependence. In the positive dependence regime, we have $\lambda_1^{LL} = w_1 \times 2^{-\frac{1}{\alpha_1}}$ and $\lambda_2^{RR} = (1-w_1) \times 2^{-\frac{1}{\alpha_2}}$, where $\lambda_1^{LL}$ and $\lambda_2^{RR}$ are the left (lower) and right (upper) tail dependence coefficients, respectively. They measure the dependence when both variables are at the lower or upper end of the spectrum respectively. $\lambda_2^{RR}$ is crucial for identifying safe haven currencies as it corresponds to situations where market risk is extremely high and the base currency appreciates.

In the negative dependence regime, we have $\lambda_3^{RL} = w_2 \times 2^{-\frac{1}{\alpha_3}}$ and $\lambda_4^{LR} = (1 - w_2) \times 2^{-\frac{1}{\alpha_4}}$, where $\lambda_3^{RL}$ measures the dependence when volatility (market risk) is overly high while the currency significantly depreciates in value, indicating a non-safe haven currency. We estimate these tail dependence parameters by employing the dependence switching copula model described above.

Figure 1: Schematic of dependence regimes




*Notes*: The coefficient of tail dependence is denoted by $\lambda_k^{\cdot\cdot}$. The right and left tails of the distribution are denoted by $R$ and $L$. The parameter $\lambda_2^{RR} = (1 - w_1) \times 2^{-\frac{1}{\alpha_2}}$ is associated with the safe haven behaviour of the USD and $\lambda_3^{RL} = w_2 \times 2^{-\frac{1}{\alpha_3}}$ with that of the other currencies. When the VIX is low, the tail dependence is estimated with $\lambda_1^{LL} = w_1 \times 2^{-\frac{1}{\alpha_1}}$ and $\lambda_4^{LR} = (1 - w_2) \times 2^{-\frac{1}{\alpha_4}}$.

Figure 1 summarizes the dependence structure of the regime-switching copula model. The first and fourth quadrants of Figure 1 are particularly crucial for identifying safe haven currencies, as they represent extremely high VIX levels with heightened market risk. The exchange rate is expressed as the value of the quote currency per unit of the base currency. In the first quadrant, when the VIX is high, the base currency appreciates, indicating its safe haven status. Conversely, in the fourth quadrant, the quote currency appreciates when the VIX is high, indicative of the safe haven status of the quote currency.

### 2.3 Marginal model and the empirical CDF

To remove possible serial correlation and heteroscedasticity from the data in order to obtain the independent and identically distributed (i.i.d.) inputs for the copulas, we specify an ARMA(1,1)-GARCH(1,1) model with the Generalized Error Distribution (GED) for the marginal model. Let $x_{1,t}$ and $x_{2,t}$ denote the measure of market risk and the log difference of the FX rate variable. The mean process follows an ARMA$(1,1)$ for both series as

$$x_{i,t} = \mu_i + \phi_i x_{i,t-1} + \varphi_i \epsilon_{i,t-1} + \epsilon_{i,t};\ \epsilon_{i,t}|I_{i,t-1} \sim e;\ i = 1, 2, \tag{5}$$

where $I_{i,t-1}$ is the information available at time $t-1$ for $i$ and $\mu_i$ is the time-invariant intercept. $\phi_i$ and $\varphi_i$ are coefficients.

The GARCH(1,1) process for the conditional variance of $\epsilon_{i,t}$ is

$$h_{i,t} = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1};\ i = 1, 2, \tag{6}$$

where $\omega_i$ is the intercept and $h_{i,t}$ is the variance of $\epsilon_{i,t}|I_{i,t-1}$. The coefficients $\alpha_i$ and $\beta_i$ correspond to the ARCH and the GARCH terms, respectively. We use the GED for the innovations to capture the heavy tails in the data (see Nelson (1991)). The GED density is as follows:

$$f(z|\nu) = \varkappa(\nu) \times \exp\big[-2^{-1}|z \times \varrho_{\nu}^{-1}|^{\nu}\big], \ -\infty < z < \infty, \ \nu > 0, \tag{7}$$

where $\nu$ is a tail-thickness parameter and $\varkappa(\nu)$ and $\varrho_{\nu}$ are given by

$$\varrho_{\nu} = [2^{-\frac{2}{\nu}}\Gamma(\nu^{-1})[\Gamma(3\nu^{-1})]^{-1}]^{\frac{1}{2}} \text{ and } \varkappa(\nu) = \nu[\varrho_{\nu} \times 2^{1+v^{-1}}\Gamma(\nu^{-1})]^{-1}, \tag{8}$$

where $\Gamma(\cdot)$ is a gamma function. The GED can be transformed into the skewed version based on the transformation of Fernández and Steel (1998). We denote the skewness parameter with $\zeta$ and the parameter vector of the marginal model with $\boldsymbol{\theta}_i^M = (\mu_i, ..., \nu_i)'$. We utilize the robust standard errors according to the quasi-maximum likelihood (QML) method in the context of Bollerslev and Wooldridge (1992).

To avoid misidentification, following literature (see (Chen and Fan, 2006)), the margins of the standardized residuals $F_1$ and $F_2$ are estimated nonparametrically by the empirical cumulative distribution function (ECDF) of the standardized residuals $z_{i,t}$, obtaining uniformly distributed $u_{i,t}$= $F_i(z_{i,t}; \boldsymbol{\theta}_i^M | I_{i,t-1})$ as follows:

$$\hat{F}_i(z_{i,t}; \boldsymbol{\theta}_i^M | I_{i,t-1}) = \frac{1}{T+1}\sum_{n=1}^{T} \mathbf{1}(z_{i,n} \leq z_{i,t}), \tag{9}$$

for $i = 1, 2$, where $\mathbf{1}(\cdot)$ is an indicator function, which takes the value 1 when its argument is true and 0 otherwise.

## 2.4 Estimation

The density of the dependence-switching copula model can be expressed as follows

$$f(x_{1,t}, x_{2,t}; \boldsymbol{\theta}^M, \boldsymbol{\theta}^C, \boldsymbol{\Pi}|I_{t-1}) = \left(\sum_{j=0}^{1} \Pr(S_t = j|I_{t-1}; \boldsymbol{\Theta}) \times c_j(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_j^C, \boldsymbol{\Pi}|I_{t-1})\right)\left(\prod_{i=1}^{2} f_i(x_{i,t}; \boldsymbol{\theta}_i^M|I_{i,t-1})\right), \tag{10}$$

where $\boldsymbol{\theta}^C = (\boldsymbol{\theta}_1^C, \boldsymbol{\theta}_0^C)$, $\boldsymbol{\theta}^M = (\boldsymbol{\theta}_1^M, \boldsymbol{\theta}_2^M)$, and $\boldsymbol{\Theta} = (\boldsymbol{\theta}^M, \boldsymbol{\theta}^C, \boldsymbol{\Pi})$. The function $c_j$ is the copula density function under regime $j$ with parameter set $\boldsymbol{\theta}_j^C$. The log-likelihood function of (10) is

$$\begin{aligned} L(\boldsymbol{\Theta}; I_T) &= L_C(u_{1,t}, u_{2,t}, \boldsymbol{\theta}^C, \boldsymbol{\Pi}; I_T) + \sum_{i=1}^{2} L_i(\boldsymbol{\theta}_i^M; I_{i,T}), \\ &= L_C(u_{1,t}, u_{2,t}, \boldsymbol{\theta}^C, \boldsymbol{\Pi}; I_T) + \sum_{i=1}^{2}\sum_{t=1}^{T} \log(f_i(x_{i,t}; \boldsymbol{\theta}_i^M|I_{i,t-1})), \end{aligned} \tag{11}$$

where $L_C$ and $L_i$ are the log of the copula density and the marginal density, respectively. We can obtain the unconditional copula density by integrating as follows:

$$L_C(u_{1,t}, u_{2,t}, \boldsymbol{\theta}^C, \boldsymbol{\Pi}; I_T) = \sum_{t=1}^{T}\sum_{j=0}^{1}[\log[\Pr(S_t = j|I_{t-1}; \boldsymbol{\Theta}) \times c_j(u_{1,t}, u_{2,t}; \boldsymbol{\theta}_j^C, \boldsymbol{\Pi}|I_{t-1})]]. \tag{12}$$

To execute Markov-switching dependence, we apply a Hamilton filter to the copula segment. For an excellent overview of this procedure, please refer to Hamilton (1990, 1994).

The optimal inference and forecast for each period $t$ in the sample period can be found by iterating on the following pair of equations:

$$\hat{\boldsymbol{\xi}}_{t|t} = \left[\hat{\boldsymbol{\xi}}'_{t|t-1}\boldsymbol{\eta}_t\right]^{-1}\hat{\boldsymbol{\xi}}_{t|t-1} \odot \boldsymbol{\eta}_t, \tag{13}$$

$$\hat{\boldsymbol{\xi}}_{t+1|t} = \boldsymbol{\Pi}' \cdot \hat{\boldsymbol{\xi}}_{t|t}, \tag{14}$$

where $\odot$ is the Hadamard product, and $\boldsymbol{\eta}_t$ represents the density of the conditional copula in (12) given the state. Precisely, $\boldsymbol{\eta}_t$ takes the form

$$\boldsymbol{\eta}_t = \begin{bmatrix} c_1(u_{1,t}(\boldsymbol{\theta}_1^M), u_{2,t}(\boldsymbol{\theta}_2^M); \boldsymbol{\theta}_1^C, \boldsymbol{\Pi}|I_{t-1}) \\ c_0(u_{1,t}(\boldsymbol{\theta}_1^M), u_{2,t}(\boldsymbol{\theta}_2^M); \boldsymbol{\theta}_0^C, \boldsymbol{\Pi}|I_{t-1}) \end{bmatrix}, \tag{15}$$

and we need standard uniformly distributed inputs for the copula density as indicated by the Canonical Maximum Likelihood (CML) approach.

The vector $\hat{\boldsymbol{\xi}}_{t|t}$ contains the probabilities of being in either state 1 or 0, given all the information up to the current period ($I_t$) and the parameter set $\boldsymbol{\theta}^C$. Analogously, $\hat{\boldsymbol{\xi}}_{t+1|t}$ holds the probabilities of being in either state at time $t+1$. Specifically, $\hat{\boldsymbol{\xi}}_{t|t}$ and $\hat{\boldsymbol{\xi}}_{t+1|t}$ take the forms

$$\hat{\boldsymbol{\xi}}_{t|t} = \begin{bmatrix} \Pr(S_t = 1|I_t; \boldsymbol{\theta}^M, \boldsymbol{\theta}_1^C, \boldsymbol{\Pi}) \\ \Pr(S_t = 0|I_t; \boldsymbol{\theta}^M, \boldsymbol{\theta}_0^C, \boldsymbol{\Pi}) \end{bmatrix}, \tag{16}$$

$$\hat{\boldsymbol{\xi}}_{t+1|t} = \begin{bmatrix} \Pr(S_{t+1} = 1|I_t; \boldsymbol{\theta}^M, \boldsymbol{\theta}_1^C, \boldsymbol{\Pi}) \\ \Pr(S_{t+1} = 0|I_t; \boldsymbol{\theta}^M, \boldsymbol{\theta}_0^C, \boldsymbol{\Pi}) \end{bmatrix}. \tag{17}$$

Using numerical methods, we can obtain the maximum likelihood estimates of the joint model parameters through either the Newton–Raphson, quasi-Newton or simplex methods. Since the marginal distributions are separable from the copula model, we use a two-step procedure for the estimation, namely the inference functions for margins (IFM) approach, see Joe and Xu (1996) and Joe (2014). In the first step, we estimate the marginal models and the ECDF of the standardized residuals from the marginal model. In the second step, we estimate the parameters of the mixture copulas ($\boldsymbol{\theta}_1^C, \boldsymbol{\theta}_0^C$) and the transition matrix ($\mathbf{\Pi}$) with inputs of the ECDFs estimated from the first step. Mathematically, the two-step estimation can be expressed as follows:

$$\hat{\boldsymbol{\theta}}^M = \underset{\boldsymbol{\theta}^M \in \mathbf{\Theta}^M}{\arg\max} \sum_{i=1}^{2} L_i(\boldsymbol{\theta}_i^M; I_{i,T}), \tag{18}$$

$$\hat{\boldsymbol{\psi}} = \underset{\boldsymbol{\psi} \in \mathbf{\Psi}}{\arg\max}\, L_C(\hat{u}_{1,t}, \hat{u}_{2,t}, \boldsymbol{\theta}^C, \mathbf{\Pi}; I_T), \tag{19}$$

where $\boldsymbol{\psi} = (\boldsymbol{\theta}^C, \mathbf{\Pi})$. $\mathbf{\Theta}^M$ and $\mathbf{\Psi}$ denote the sets of possible values of $\boldsymbol{\theta}^M$ and $\boldsymbol{\psi}$, respectively. As shown by Joe (1997), under certain regularity conditions, the IFM estimator exists and is consistent and asymptotically normal. For a discussion on efficiency, refer to Joe (2005) and Patton (2009).

In general, we have

$$\sqrt{T}(\hat{\mathbf{\Theta}} - \mathbf{\Theta}_0) \xrightarrow{d} N(\mathbf{0}, -\mathbf{H}^{-1}(\mathbf{\Theta}_0)), \text{ for } t \to \infty,$$

where $\hat{\mathbf{\Theta}}$ is any consistent estimator of the full parameter set, and $\mathbf{H}^{-1}(\mathbf{\Theta}_0)$ is the inverse of the Hessian (Bierens, 2004; Cherubini et al., 2004; Martin et al., 2013). For a derivation of the above result, refer to Joe (2014). We employ the delta method to compute the standard errors of the joint parameter estimates. Assume that $\{\hat{\mathbf{\Theta}}_N\}$ is a sequence of $V \times 1$ random vectors such that

$$\sqrt{T}(\hat{\mathbf{\Theta}}_N - \mathbf{\Theta}_0) \xrightarrow{d} N(\mathbf{0}, -\mathbf{H}^{-1}(\mathbf{\Theta}_0)), \text{ for } t \to \infty.$$

Let $\mathbf{g} : \mathbb{R}^V \to \mathbb{R}^W$ be a continuously differentiable function in $W$ dimensions with respect to $\mathbf{\Theta}$, then

$$\sqrt{T}(\mathbf{g}(\hat{\mathbf{\Theta}}_N) - \mathbf{g}(\mathbf{\Theta}_0)) \xrightarrow{d} N(\mathbf{0}, [\mathbf{J_g}(\mathbf{\Theta}_0)][-\mathbf{H}^{-1}(\mathbf{\Theta}_0)][\mathbf{J_g}(\mathbf{\Theta}_0)]'), \text{ for } t \to \infty,$$

where $\mathbf{J_g}$ is the Jacobian of $\mathbf{g}$, i.e., the $W \times V$ matrix of partial derivatives of $\mathbf{g}$ in relation to the entries of $\mathbf{\Theta}$. For a more detailed account, refer to Wooldridge (2010), Yee (2015), and Hansen (2022).

# 3 Data

We consider five potential safe haven currencies, which involve four exchange rates in terms of one USD, namely the EUR, the GBP, the JPY, and the CHF per unit of the USD. Thus, the base currency is the USD, and the others are the quote currencies. The data are obtained from Thomson Reuters. In addition, we gather data on the Federal Reserve dollar indexes from the Federal Reserve System website. The broad dollar index (Broad), is constructed using the currencies of the most important US trading partners by volume of bilateral trade. We chose the broad index for our principal analysis since it is more inclusive.

The market risk proxies are the VIX, the Euro Stoxx 50 Volatility Index (V2X), and the Volatility Index on the Swiss Market Index (VSMI), sourced from CBOE, SIX Group, and Qontigo, respectively. The VIX is constructed from the implied volatility of option prices on the S&P 500 over the next 30 days. The V2X and the VSMI are created similarly to the VIX but based on 50 blue chip euro zone stocks and the 20 largest Swiss stocks, respectively. The frequency of the data is daily, and the time span is from January 01, 1999, to December 12, 2022.

Figure 2a plots the per USD exchange rates for the euro, the pound, and the CHF, whereas Figure 2b displays the exchange rate of yen per USD. The graphs show that all four exchange rates fluctuated substantially. The euro, pound, and franc depreciated against the USD around the 2001 tech bubble, the 2008 financial crisis, and the onset of the pandemic, giving evidence contrary to safe havens or of less strong safe havens than the USD. On the other hand, the Japanese yen appreciated against the USD for the periods of 1999–2000, 2007–2011, and 2019–2020, showing evidence that it is a more vital safe haven than the USD during these periods. Figure 2c provides the three USD indexes, which are highly correlated. We can also see that the USD indexes appreciated during several crises or market turmoil periods, including the 2001 tech bubble, 2008 financial crises, and the pandemic period, which is evidence of a safe haven currency.

Figure 3 plots the volatility indexes. It is clear from the graph that the three volatility indexes are highly correlated. Table 1 presents the correlations between these indexes. As depicted in Figure 3 and consistent with existing literature (see Habib and Stracca (2012), Fatum and Yamamoto (2016), and Wong and Fong (2018)), the correlations between VIX and the other two market risk proxies are very high close to 1. Therefore, we use VIX as the proxy for market risk.

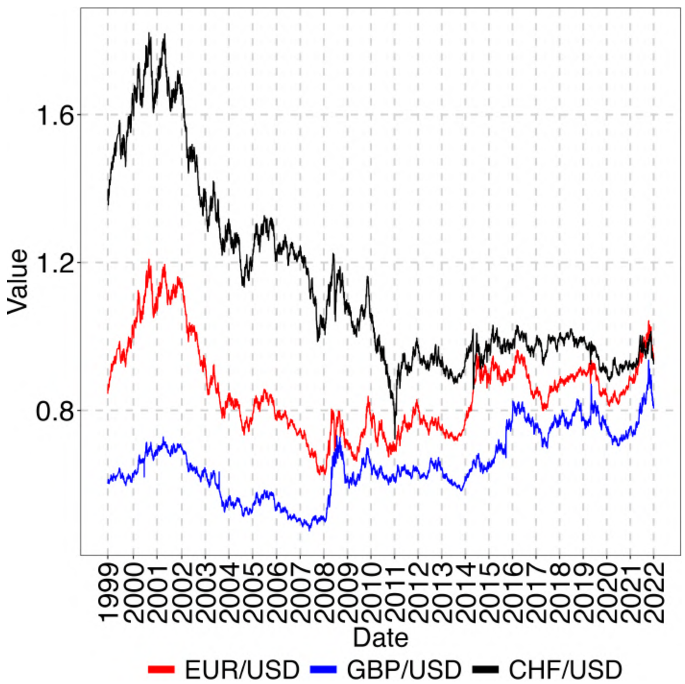
Table 1: Correlations between volatility indexes

| | VIX | V2X | VSMI |
|---|---|---|---|
| VIX | 1.000 | 0.900 | 0.894 |
| V2X | 0.900 | 1.000 | 0.947 |
| VSMI | 0.894 | 0.947 | 1.000 |

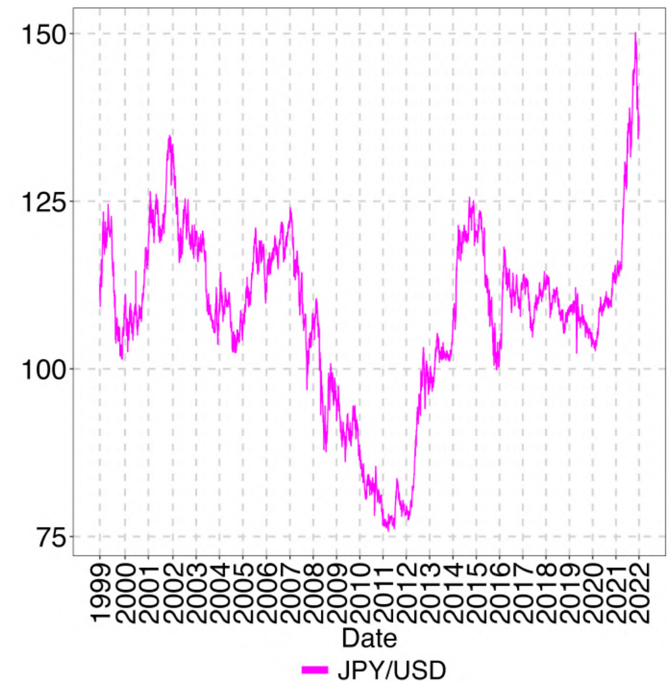
*Notes*: The VIX is the CBOE's volatility index. V2X and VSMI denote the volatility indexes of the Euro Stoxx 50 and Swiss Market Index, respectively.

Figure 2: Data graph

(a) Euro, pound, franc




(b) Yen




(c) Trade-weighted USD

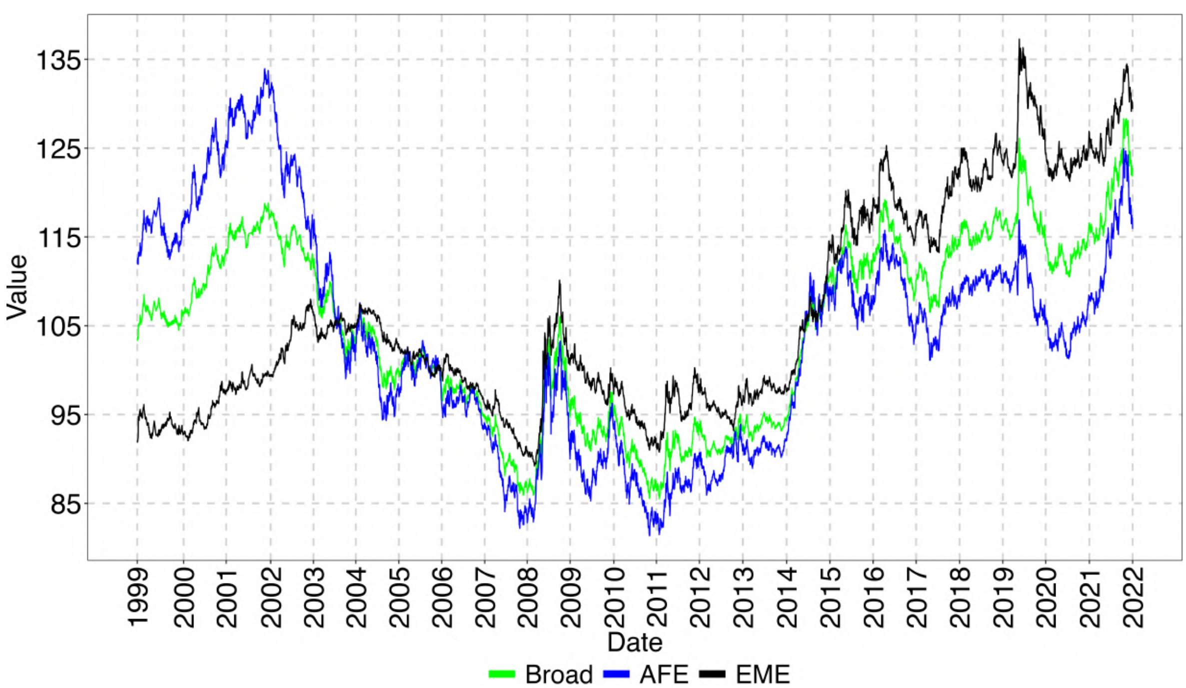


Figure 3: Volatility indexes

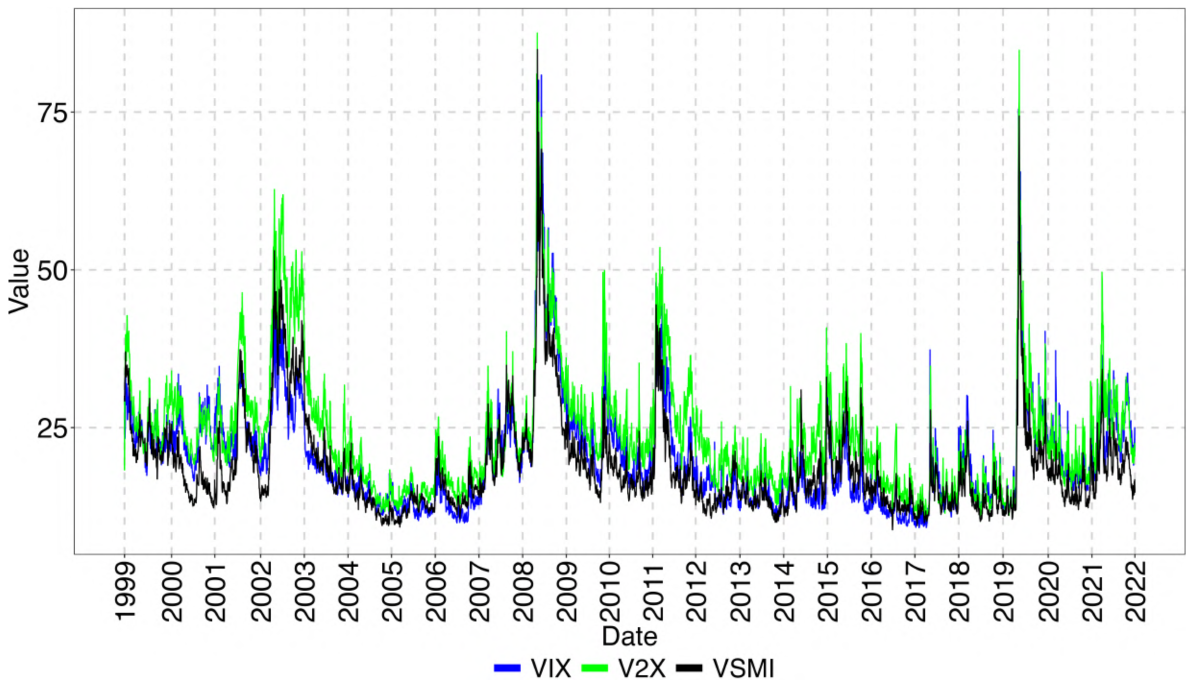



Table 2: Summary statistics of the variables

| | Mean | Std | Skewness | Kurtosis | Min | Max | JB |
|---|---|---|---|---|---|---|---|
| VIX | 20.322 | 8.567 | 2.083 | 7.568 | 9.140 | 82.690 | 18,437.650*** |
| EUR/USD | 0.002 | 0.602 | -0.034 | 2.543 | -4.617 | 3.844 | 1,600.236*** |
| GBP/USD | 0.005 | 0.633 | 0.634 | 23.193 | -7.943 | 8.410 | 133,269.600*** |
| CHF/USD | -0.007 | 0.677 | -2.548 | 76.497 | -17.137 | 8.929 | 1,451,835.000*** |
| JPY/USD | 0.003 | 0.642 | -0.337 | 6.104 | -5.562 | 5.854 | 9,317.640*** |
| TW-USD | 0.003 | 0.328 | 0.022 | 4.282 | -2.553 | 1.893 | 4,530.762*** |

*Notes*: The daily data is from January 01, 1999, to December 12, 2022. We denote the Jarque–Bera statistic with JB, and the rejection of the null that the data is distributed normally at a 1% significance level is signified by three asterisks.

Table 2 presents the summary statistics of the variables. The exchange rates and the trade-weighted USD (TW-USD) are their returns computed by taking log differences and are expressed in percentages. All variables exhibit positive excess kurtosis, with the CHF/USD and the GBP/USD showing extremely high excess kurtosis of 76.497 and 23.193, respectively. This indicates that all variables are highly leptokurtic and have fat tails. Also, all currency returns are negatively skewed. According to (Coudert et al., 2014; Hossfeld and MacDonald, 2015), the market is considered to be in turmoil if the VIX is above 30. In our sample period, the VIX ranges from 9.14 to 82.69, suggesting periods of high market turmoil. The skewness and kurtosis of the variables suggest that our variables are not normally distributed, a conclusion supported by the Jarque–Bera normality test results presented in the last column of the table.

Table 3: Dependence measures between the currencies and the VIX

| | EUR/USD | GBP/USD | CHF/USD | JPY/USD | TW-USD |
|---|---|---|---|---|---|
| Linear correlation | 0.026 | 0.063 | 0.003 | -0.049 | 0.079 |
| Spearman's $\rho$ | 0.013 | 0.027 | 0.002 | -0.039 | 0.039 |
| Kendall's $\tau$ | 0.009 | 0.018 | 0.001 | -0.027 | 0.026 |

*Notes*: The dependence measures provided above are the nonparametric versions. For every column, one input is always the VIX and the second input varies based on the variable given in the header.

Table 3 provides three dependence measures between exchange rate returns and the VIX. All dependence measures are positive except for the yen per USD, indicating that when the VIX increases, the USD tends to appreciate against the euro, the pound, or the franc, while the yen appreciates against the USD. This suggests that the JPY may be a stronger safe haven currency compared to the USD.

# 4 Empirical results

Table 4 provides the results for the marginal models. The parameter estimates for the ARMA terms, GARCH terms, and the GED are significant for all variables. Thus, the marginal models remove the variables' serial correlations, heteroskedasticity and fat tails. This well prepares the standardized residuals from the marginal models for the joint copula model.

Figure 4 presents the joint empirical cumulative distribution function (ECDF) of exchange rate returns and the VIX. In this figure, the concentration of observations in each corner of the bivariate distribution indicates the density of the tails. The cutoff for the left (lower) side of the distribution is the 10%-quantile, and for the right (upper) side is the 90%-quantile, for instance, the left–upper corner corresponds to the tail region of [0%–10%-quantiles, and 90%–100%-quantiles]. Figure 4 clearly shows that the right–upper and the right–lower regions are denser than the other two sections. Since our exchange rates are in terms of USD, the upper–right corner is associated with USD appreciation when the VIX is high, while the lower right corner signifies non-USD currency appreciation during high VIX periods. Therefore, the right–upper or left–lower corners support the safe haven properties of the base and quote currencies, respectively.

The graphs reveal that the percentage of observations falling into the right–upper corner is higher than those in the right–lower corner for all pairs except for JPY/USD. For example, the values associated with the right–upper and right–lower corners for EUR/USD are 0.0189 and 0.0155, respectively. The comparison of mass in the right–upper and right–lower corners suggests that during periods of extremely high market risk, the USD appreciates more than the euro, the pound, and the CHF, while the JPY appreciates more than the USD, indicating the stronger safe haven status of the USD compared to the euro, the pound, and the franc, with the JPY being an even

Table 4: ARMA(1,1)-GARCH(1,1) with a skewed GED innovation

| | *Response variable:* | | | | | |
|---|---|---|---|---|---|---|
| | VIX | EUR/USD | GBP/USD | CHF/USD | JPY/USD | TW-USD |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mu$ | 16.911$^{***}$ | −0.001 | 0.001 | −0.007 | 0.006 | 0.001 |
| | (0.768) | (0.007) | (0.008) | (0.007) | (0.004) | (0.004) |
| $\phi$ | 0.981$^{***}$ | 0.746$^{***}$ | 0.951$^{***}$ | −0.657$^{***}$ | 0.603$^{***}$ | 0.271$^{***}$ |
| | (0.003) | (0.015) | (0.013) | (0.113) | (0.008) | (0.008) |
| $\varphi$ | −0.120$^{***}$ | −0.755$^{***}$ | −0.956$^{***}$ | 0.638$^{***}$ | −0.636$^{***}$ | −0.243$^{***}$ |
| | (0.014) | (0.014) | (0.005) | (0.115) | (0.008) | (0.009) |
| $\omega$ | 0.076$^{***}$ | 0.001$^{**}$ | 0.005 | 0.003$^{***}$ | 0.003 | 0.001$^{***}$ |
| | (0.013) | (0.0004) | (0.028) | (0.001) | (0.002) | (0.0002) |
| $\alpha$ | 0.215$^{***}$ | 0.034$^{***}$ | 0.048 | 0.036$^{***}$ | 0.048$^{***}$ | 0.044$^{***}$ |
| | (0.016) | (0.002) | (0.152) | (0.003) | (0.018) | (0.005) |
| $\beta$ | 0.759$^{***}$ | 0.964$^{***}$ | 0.938$^{***}$ | 0.957$^{***}$ | 0.944$^{***}$ | 0.950$^{***}$ |
| | (0.017) | (0.0002) | (0.227) | (0.0005) | (0.023) | (0.005) |
| $\zeta$ | 1.282$^{***}$ | 1.020$^{***}$ | 1.033$^{***}$ | 0.930$^{***}$ | 0.972$^{***}$ | 1.033$^{***}$ |
| | (0.031) | (0.017) | (0.035) | (0.015) | (0.014) | (0.019) |
| $\nu$ | 1.183$^{***}$ | 1.512$^{***}$ | 1.278$^{***}$ | 2.000$^{***}$ | 1.220$^{***}$ | 1.459$^{***}$ |
| | (0.042) | (0.043) | (0.094) | (0.082) | (0.044) | (0.048) |
| $T$ | 5,924 | 5,924 | 5,924 | 5,924 | 5,924 | 5,924 |
| LL | −8,066.641 | −4,898.523 | −4,871.748 | −5,203.596 | −5,132.129 | −1,137.604 |
| AIC | 3.115 | 1.656 | 1.647 | 1.759 | 1.735 | 0.387 |
| BIC | 3.125 | 1.666 | 1.656 | 1.769 | 1.744 | 0.396 |

*Notes*: *, **, and *** denote significance at 10%, 5%, and 1%, respectively. In sequential order, the first set of parameters is the mean intercept ($\mu$), the AR ($\phi$) and the MA ($\varphi$) coefficients of the ARMA model. The next set of parameters is for the GARCH model: the dispersion intercept ($\omega$), the ARCH term ($\alpha$), and the GARCH term ($\beta$). The skewness and the degrees of freedom parameters are denoted by $\zeta$ and $\nu$, respectively. The standard errors are in parentheses. $T$ is the number of observations. LL, AIC, and BIC denote the estimated log-likelihood value, the Akaike information criterion, and the Bayesian information criterion, respectively.

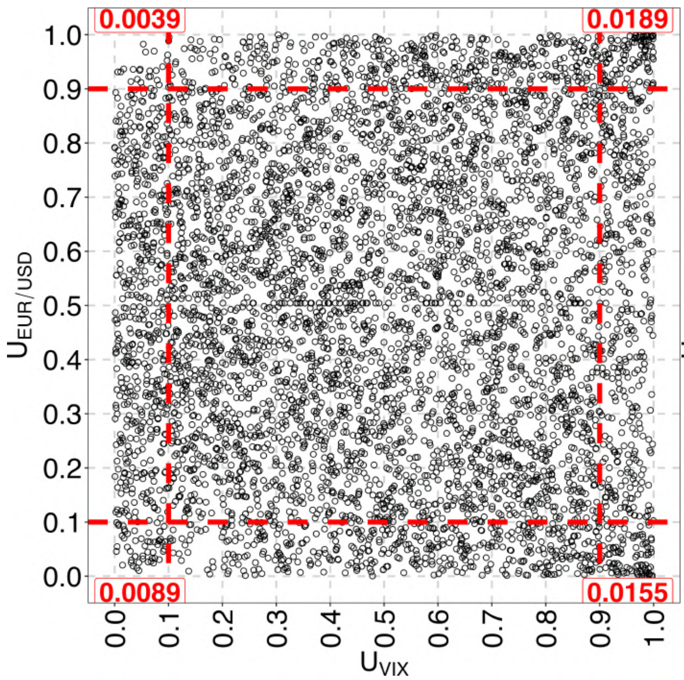
stronger safe haven than the USD. These results are consistent with Fratzscher (2009), De Bock and de Carvalho Filho (2015), Fatum and Yamamoto (2016), and Tachibana (2018). Although the USD significantly overshadows the safe haven behaviour of the euro, the pound, and, to a lesser extent, the franc, these currencies also exhibit their own safe haven characteristics, as evidenced by the clustering of observations in the right–lower corner.

Table 5 provides the estimates of our joint model. Clearly, a vast majority of the parameter estimates are statistically significant. The two most relevant parameters used to measure the safe haven properties are $\lambda_2^{RR}$ and $\lambda_3^{RL}$, which are significant for all currencies. $\lambda_2^{RR}$ and $\lambda_3^{RL}$ represent when the market risk is exceptionally high, the base currency (the USD) appreciates or the quote currency appreciates, respectively. The significance of both parameters indicates that all currencies show safe haven properties. In addition, except for the JPY, the estimates of the tail dependence coefficient $\lambda_2^{RR}$ are larger than $\lambda_3^{RL}$, where the former is associated with the safe haven behaviour of the USD and the latter with that of the quote currencies. For example, the estimates of $\lambda_2^{RR}$ are 0.051 and 0.108 for the euro and the pound, respectively, much stronger than $\lambda_3^{RL}$, which are 0.037 and 0.045, respectively. This indicates that the USD is a safe haven currency relative to the euro and the pound. Our joint parameter estimates for the trade-weighted USD are consistent with the safe haven nature of the dollar since they indicate that the value of the USD index increases when there is heightened global risk aversion, as suggested by the parameter estimate of $\lambda_2^{RR}$ (0.100) relative to all other tail dependence coefficients.

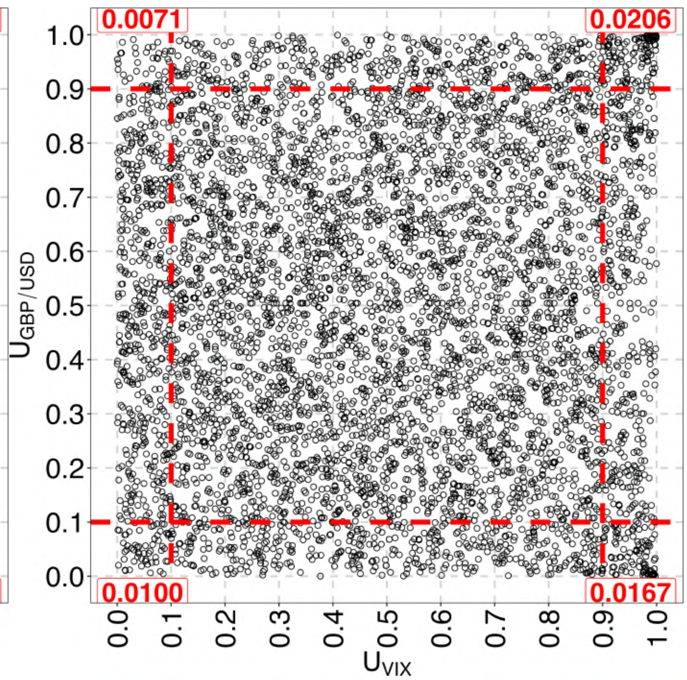
For the CHF, the estimates of $\lambda_2^{RR}$ and $\lambda_3^{RL}$ are 0.036 and 0.029, respectively, which do not substantially differ, implying that it is slightly weaker than the USD as a safe haven (also, please refer to Figure 4c for the joint ECDF estimates). On the other hand, the JPY is the anomaly whose $\hat{\lambda}_2^{RR}$ (0.033) is significantly below $\hat{\lambda}_3^{RL}$ (0.045), indicating that the JPY displays considerable safe

Figure 4: ECDF

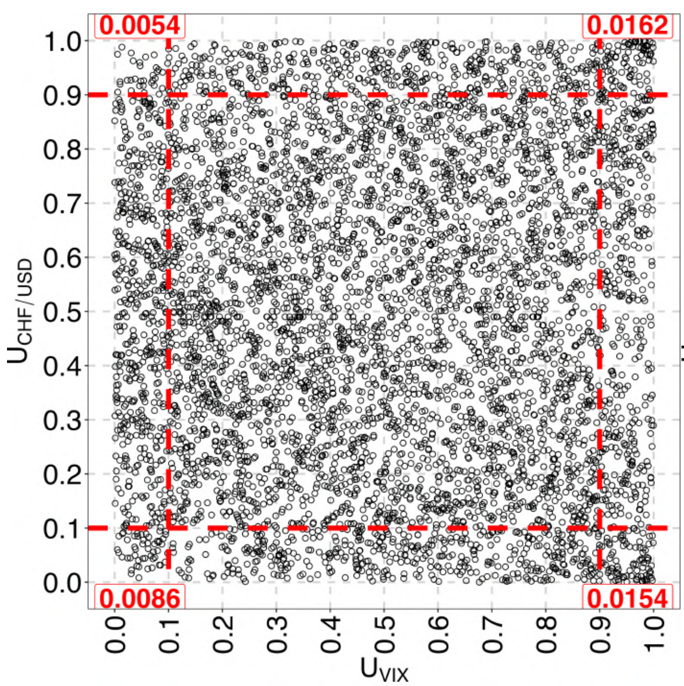
(a) EUR/USD




(b) GBP/USD




(c) CHF/USD




(d) JPY/USD

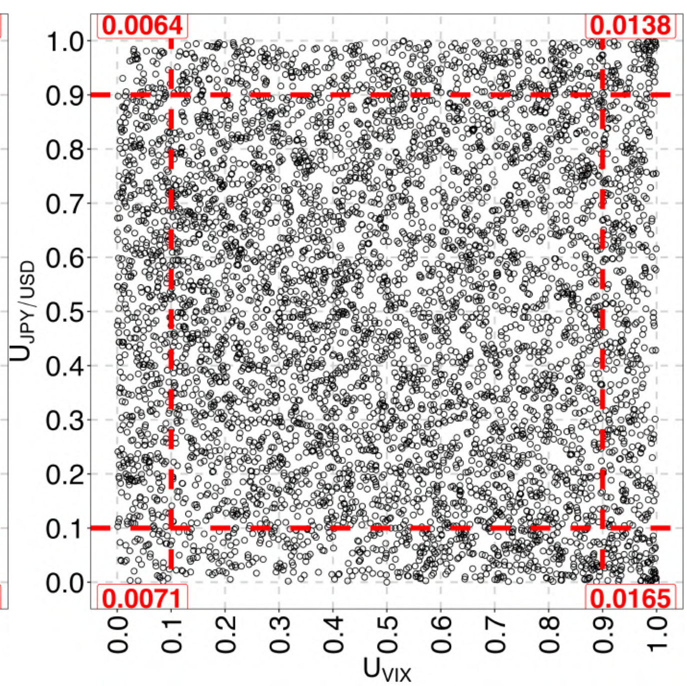
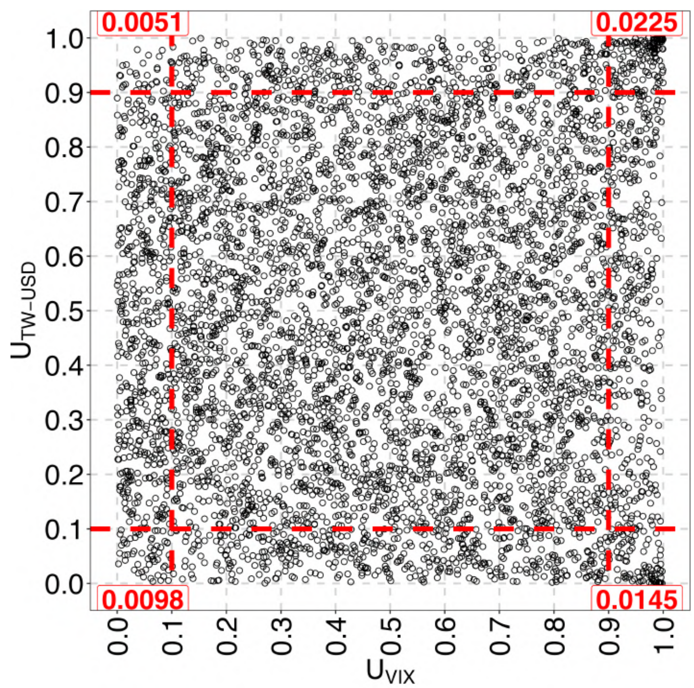


Figure 4: ECDF (*continued*)

(e) TW-USD



haven attributes. In fact, the JPY is the only currency that is not overpowered by the safe haven character of the USD. These results are consistent with our prior joint ECDF results.

These findings are consistent with previous studies, such as Coudert et al. (2014), Fatum and Yamamoto (2016), and Wong and Fong (2018), regarding the status or strength of the JPY as a safe haven currency. However, there is disagreement regarding the CHF's classification as a safe haven, although there is consensus that the USD possesses safe haven properties. Our results suggest that the CHF exhibits weaker safe haven behaviour than the yen and the USD. The significance of $\lambda_3^{RL}$ for the euro and pound indicates that they are both safe havens though, weaker than the USD and the JPY. This partially differs from Ranaldo and Söderlind's (2010) findings, which suggest that the euro has weaker safe haven characteristics than the CHF and the JPY, and the pound may not be considered as a safe haven.

The correlation coefficient ($\rho_k$) reflects the linear dependence observed in various quadrants. The higher estimated value for $\rho_2$ than $\rho_3$ suggests that, on average, the appreciation of the USD during periods of increasing volatility is generally weaker compared to the quote currencies. However, the stronger tail dependence coefficient, $\lambda_2^{RR}$, relative to $\lambda_3^{RL}$, indicates that the extreme appreciation of the USD when market risk is exceptionally high is much stronger than that of the quote currencies, suggesting a stronger safe haven status of the USD. Furthermore, the transition probability of remaining in the positive dependence state is higher than that in the negative dependence regime, indicating more extended periods of USD appreciation compared to the quote currencies when the VIX is high. This is also supported by the higher weight ($w_1$) in the right–upper dependence quadrant compared to the weight ($w_2$) in the right–lower dependence quadrant. Therefore, our method of using tail dependence and dependence-switching copula models to identify safe havens is more direct and practical.

Table 5: Joint model estimates

| | *Volatility and currency pairs:* | | | | |
|---|---|---|---|---|---|
| | EUR/USD | GBP/USD | CHF/USD | JPY/USD | TW-USD |
| | (1) | (2) | (3) | (4) | (5) |
| $\rho_1$ | 0.154*** | 0.141*** | 0.099*** | 0.104*** | 0.156*** |
| | (0.013) | (0.017) | (0.025) | (0.024) | (0.013) |
| $\lambda_1^{LL}$ | 0.015*** | 0.013** | 0.003 | 0.004 | 0.016*** |
| | (0.004) | (0.006) | (0.004) | (0.005) | (0.004) |
| $\rho_2$ | 0.189*** | 0.268*** | 0.184*** | 0.190*** | 0.244*** |
| | (0.025) | (0.035) | (0.042) | (0.058) | (0.026) |
| $\lambda_2^{RR}$ | 0.051** | 0.108*** | 0.036*** | 0.033*** | 0.100*** |
| | (0.020) | (0.029) | (0.010) | (0.010) | (0.024) |
| $w_1$ | 0.368*** | 0.431*** | 0.522*** | 0.600*** | 0.356*** |
| | (0.049) | (0.060) | (0.106) | (0.113) | (0.046) |
| $\Pi_{11}$ | 0.961*** | 0.961*** | 0.959*** | 0.960*** | 0.961*** |
| | (0.034) | (0.113) | (0.022) | (0.040) | (0.225) |
| $\rho_3$ | 0.279*** | 0.423*** | 0.233*** | 0.239*** | 0.333*** |
| | (0.082) | (0.107) | (0.077) | (0.048) | (0.084) |
| $\lambda_3^{RL}$ | 0.037* | 0.045*** | 0.029** | 0.045* | 0.031*** |
| | (0.020) | (0.011) | (0.010) | (0.026) | (0.011) |
| $\rho_4$ | 0.108*** | 0.097*** | 0.071*** | 0.067*** | 0.106*** |
| | (0.014) | (0.018) | (0.025) | (0.026) | (0.014) |
| $\lambda_4^{LR}$ | 0.003 | 0.002 | 0.000 | 0.000 | 0.003 |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) |
| $w_2$ | 0.179*** | 0.110*** | 0.208** | 0.305*** | 0.109*** |
| | (0.062) | (0.032) | (0.094) | (0.091) | (0.035) |
| $\Pi_{00}$ | 0.883*** | 0.885*** | 0.880*** | 0.885*** | 0.885*** |
| | (0.044) | (0.095) | (0.055) | (0.058) | (0.126) |
| LL | -10,052.11 | 7,948.459 | -10,041.72 | -10,056.38 | 7,849.611 |

*Notes*: *, **, and *** denote significance at 10%, 5%, and 1%, respectively. $\rho_k$ represents the correlation coefficient. The parameter $\lambda_k^{\cdot\cdot}$ denotes the tail dependence coefficient, where the superscript $L$ and $R$ signify the left and right tails, respectively. The weights of the mixture copulas are denoted by $w_1$ and $w_2$. $\Pi_{11}$ and $\Pi_{00}$ are the two transition probabilities between two consecutive positive dependence regimes and two consecutive negative dependence regimes, respectively. The standard errors are in round brackets. LL denotes the estimated log-likelihood value.

Figures 5a–5e present the smoothing correlations computed following Wang et al. (2013, 2018) (also see Kim (1994) and Kim et al. (1999)).[1] Clearly shown in the graphs, the correlation is positive during significant market events such as the 2000–2002 high-tech bubble, the 2008 financial crisis, and the onset of the pandemic in 2020. This again suggests that the USD demonstrates safe haven characteristics during these major market turmoil and crisis periods.

# 5 Conclusion

We further find that the yen is a safe haven currency that the USD does not overshadow. Moreover, the safe haven characteristics of the USD overshadow the safe haven behaviour of the euro, the pound, and the CHF. These findings, combined with the fact that the dollar is the most traded currency internationally, provide vital insights to various stakeholders. Given the nature of the US in global affairs, especially after the Second World War, it is somewhat unsurprising that its fiat currency is a safe harbour of value in uncertain or turbulent times.

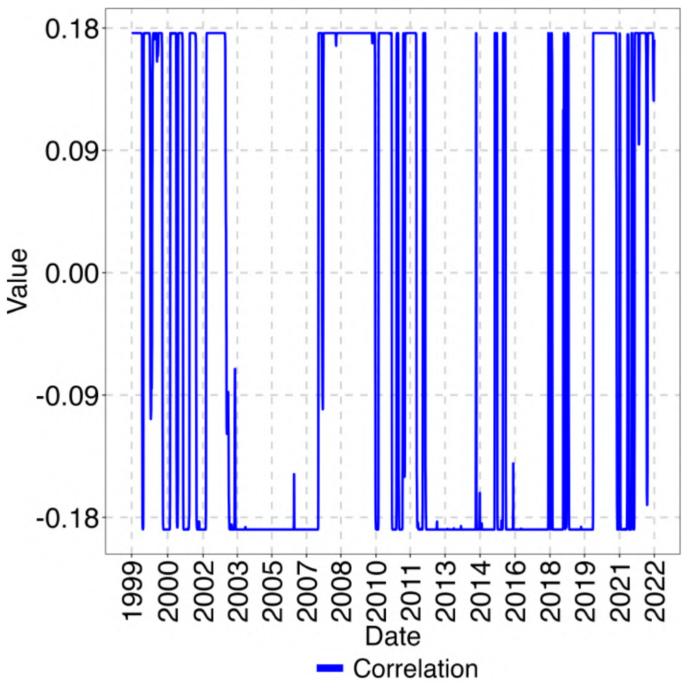
We further find the yen is a safe haven currency that is not overshadowed by the USD. On the other hand, the CHF exhibits safe haven traits to a lesser extent than both the yen and the USD. The euro and the pound display the weakest safe haven properties compared with the USD. Our results are consistent with the existing literature in that there is a broad consensus that both the dollar and the yen are safe havens. Nevertheless, we disagree with the literature and find that the pound is a safe haven, though much weaker than the USD.

This study explores essential aspects of safe haven currencies. Also, we provide valuable details

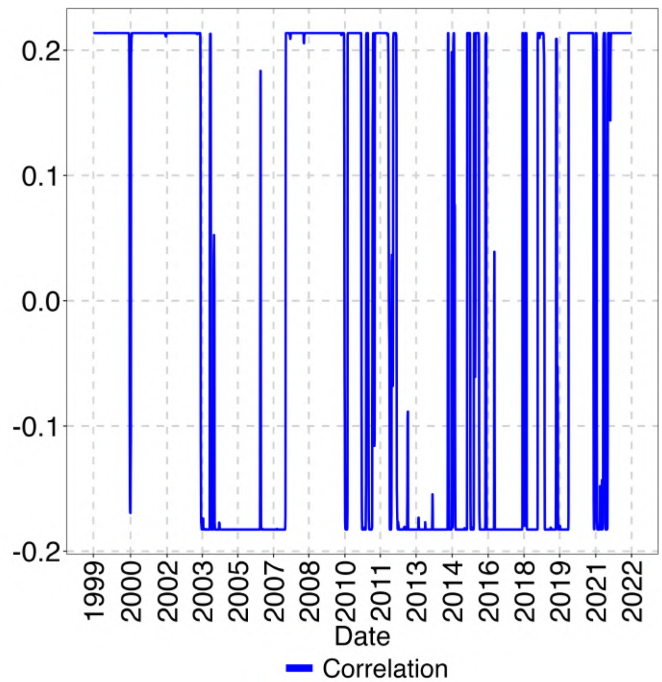
[1]For the positive dependence regime we have the following Kendall's $\tau$, i.e., $\tau^1 = w_1[\frac{\alpha_1}{2+\alpha_1}] + (1-w_1)[\frac{\alpha_2}{2+\alpha_2}]$. Similarly, for the negative dependence regime we have $\tau^0 = w_2[\frac{\alpha_3}{2+\alpha_3}] + (1-w_2)[\frac{\alpha_4}{2+\alpha_4}]$. The smoothing correlation is given by $\rho_{sm} = p_{1,sm}\sin(\frac{\pi\times\tau^1}{2}) - p_{0,sm}\sin(\frac{\pi\times\tau^0}{2})$, where $p_{\cdot,sm}$ is the smoothed probability.

Figure 5: Smoothing correlation

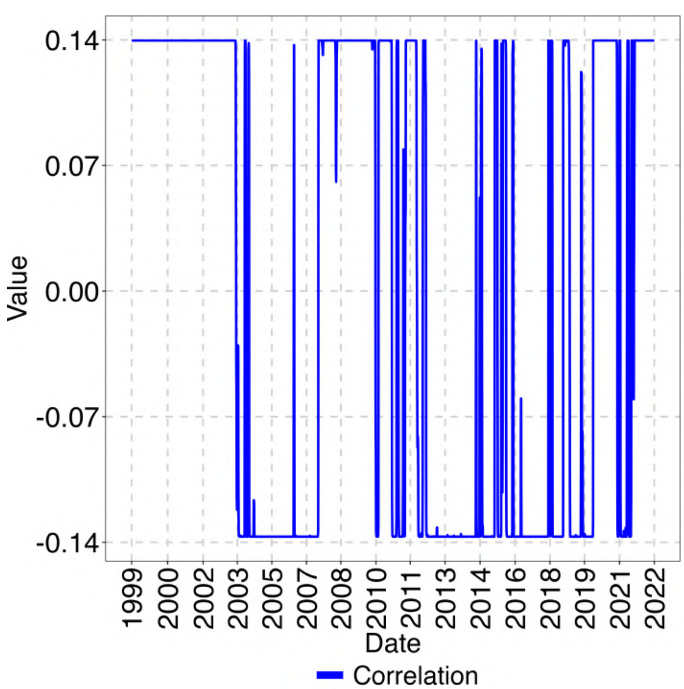
(a) EUR/USD




(b) GBP/USD




(c) CHF/USD




(d) JPY/USD

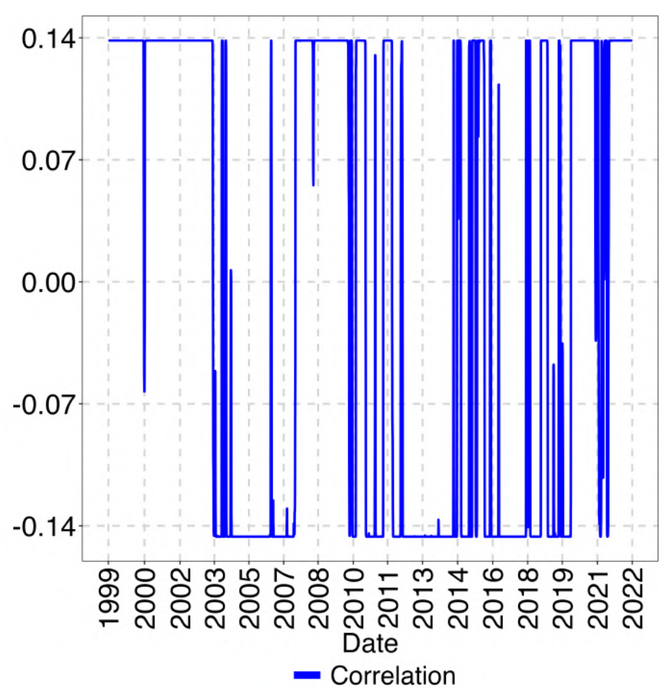
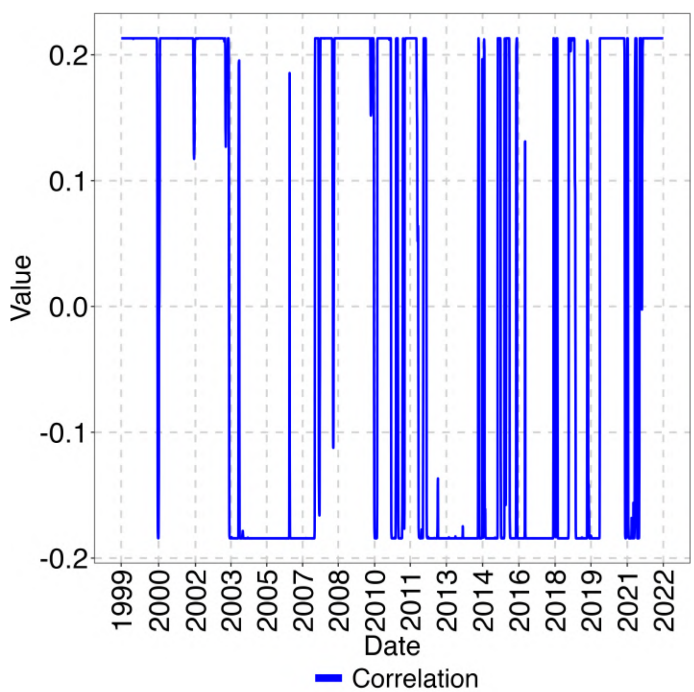


Figure 5: Smoothing correlation (*continued*)

(e) TW-USD



and a new viewpoint on different phenomena and mechanisms related to safe haven currencies. These insights are helpful for individuals to mitigate risk and avoid the detrimental effects of unexpected currency fluctuations.

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