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Relationship between stock and currency markets conditional on the US stock returns: A vine copula approach

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Abstract

Ignoring the co-movement of international stock markets might lead to a biased estimate for the relationship between domestic stock and currency markets. We address this issue by using the US stock returns as a proxy for the movement of foreign stock markets and by applying a vine copula approach to 22 economies over the period 2003–2017. We find that both stock and currency markets in these economies are highly correlated with the US stock market during the crisis period of 2007–2012. As a result, Kendall's τ correlation between domestic stock and currency returns significantly decreases in most of the economies for the crisis period, compared with the one estimated from the non-vine bivariate model without the US stock returns. This suggests that if one does not control for the effect of foreign stock markets, the resulting bias is not negligible especially in times of financial turmoil.

Keywords: Vine copula, Stock return, Currency return.

JEL Classification: C58, F31, G15.

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1 Introduction

Understanding the relationships between stock and currency markets within countries is an important issue for international investors who manage risks in their portfolios as well as for policymakers who are responsible for financial and macroeconomic stability. The literature on the subject has relied on two classical theories of exchange rate determination to explain different types of linkages between domestic stock and currency markets. The "flow-oriented" or "international-trading model" (Dornbusch and Fischer, 1980) suggests that changes in exchange rates affect the international competitiveness of firms, consequently influencing their profits and stock prices. Thus, whether the correlation between stock prices and currency values is negative or positive might depend on whether a country under study is an export-dominant or import-dominant country. On the other hand, the "stock-oriented" or "portfolio-balance model" (Branson, 1983; Frankel, 1983) predicts that increases in stock prices in a country raise investors' wealth, leading in turn to increases in money demand and interest rates, which induce appreciations of the domestic currency. Hence if this effect is dominant, we should find positive relationship between stock prices and currency values. Another and more plausible explanation from the viewpoint of international investment is that a positive shock to a country's stock market would attract capital flows from foreign investors, resulting to an appreciation of the currency to buy the stocks. Building on these theoretical insights, a vast number of empirical studies have attempted to clarify the linkages between stock and currency markets for various countries and periods. See, for instance, a review article by Bahmani-Oskooee and Saha (2015) and references therein.[1]

Most of the previous studies, however, have not considered the co-movement of international stock markets, which has been investigated by many authors in another strand of literature (e.g., Ang and Bekaert, 2002; Erb et al., 1994; Forbes and Rigobon, 2002; Ramchand

[1]Bahmani-Oskooee and Saha (2015) conclude that although the link between stock prices and exchange rates is dependent on the data frequency and period chosen, the countries studied, and other macroeconomic variables, most of the previous studies find that the two variables are related in the short-run but not in the long-run.

and Susmel, 1998; Kasa, 1992; King et al., 1994; Longin and Solnik, 1995, 2001; Solnik et al., 1996). Ignoring this factor might lead to a biased estimate for the domestic stock-currency relationship, because a common shock to international stock markets would influence a local country's stock and currency markets as well, generating a spurious positive correlation among them that is not explained by theories mentioned above. Therefore, one needs to control for the effect of foreign stock markets on both domestic stock and currency markets to obtain an unbiased estimate of the country-specific stock-currency relationship that the theories can account for.

The aim of this paper is to reveal this country-specific dependence structure between stock and currency markets. To this end, we employ a vine copula approach which has been recently developed in statistics and applied to financial data. More specifically, we construct a three-variate vine copula model that consists of a local economy's stock and currency returns and the US stock returns, and apply it to 22 economies over the period 2003–2017. Here the US stock return is used as a proxy for the movement of foreign markets, since the US stock market is largest in the world and has played a leading role in the evolution of international stock markets. The vine copula model enables us to assess the dependence structure between stock and currency returns conditional on the state of the US stock market. We compare the result from the vine copula model with that from the non-vine bivariate copula model (which does not contain the US stock returns) in order to see if there is bias in the estimate of the domestic stock-currency relationship when the latter model is estimated.

A few studies have taken into account the impact of foreign stock markets on the stock-currency relationship. Phylaktis and Ravazzolo (2005) incorporate the US stock price into the cointegration system of stock prices and exchange rates for five Asian countries (Hong Kong, Malaysia, Philippines, Singapore, and Thailand). The evidence suggests that stock and foreign exchange markets are positively related and that the US stock market acts as a conduit for these links. Diamandis and Drakos (2011) apply the same cointegration model to four Latin American countries (Argentina, Brazil, Chile, and Mexico), obtaining similar results to those in Phylaktis and Ravazzolo (2005). Kubo (2012) adds two variables of the US stock price index and the stock price index of the US information technology industry to the cointegration systems of five Asian countries (Indonesia, Korea, Philippines, Singapore, and Thailand). He finds that the two US stock price indices are positively related to the stock prices of all these countries. Moreover, he shows evidence that the relationships between domestic stock and foreign exchange markets in Indonesia, Korea, and Thailand are consistent with the portfolio-balance model. Sui and Sun (2016) estimate vector autoregressive (VAR) models with the US stock return for BRICS countries. They find significant spillover effects from exchange rates to stock returns in the short-run, but not vice versa. They also find that shocks to the US stock market significantly influence stock markets in Brazil, China, and South Africa.

This paper contributes to the literature by adopting a vine copula approach, which dates back to Joe (1996) and is further studied by Bedford and Cooke (2001, 2002), Kurowicka and Cooke (2006), Aas et al. (2009), among others. The advantage of using the vine copula approach is that it allows a great deal of flexibility and complexity in specifying a model for the joint distribution of three or more variables. More specifically, a vine copula structure decomposes a multivariate density into products of respective marginal densities and bivariate copulas, the latter characterizing dependence structures for some pairs of the variables under study. Although the class of multivariate copulas is quite restricted, a huge number of bivariate copulas have been proposed. Therefore, we can construct a flexible and complex model for a multivariate joint distribution through the vine copula approach.

Michelis and Ning (2010), Ning (2010), Reboredo et al. (2016), and Wang et al. (2013) have also adopted copula approaches to investigate the relationship between stock and currency markets. However, they estimate bivariate copula models with only two variables of stock and exchange rate returns. Meanwhile, this study extends the bivariate copula to the three-variate vine copula model with the US stock returns to control for the effect of foreign stock markets on the domestic stock-currency relationship.

Our most concern is whether the bias in the estimate of a stock-currency relationship becomes larger in times of financial turbulence than in normal times, since domestic stock and currency markets might be more strongly correlated with the US stock market or foreign stock markets during the volatile times. Many recent studies show that interdependence among stock markets in the world had been intensified during the 2007–2009 global financial crisis due to contagion effects (see, e.g., Aloui et al., 2011; Bekiros, 2014; Dimitriou et al., 2013; Karanasos et al., 2016; Kenourgios and Padhi, 2012; Kenourgios and Samitas, 2011; Kim et al., 2015; Samarakoon, 2011; Syllignakis and Kouretas, 2011; Yang and Hamori, 2013). It might also be true during the episode of the European debt crisis beginning at the end of 2009. To allow for such possible structural changes in the dependence structure among international stock markets, we divide our full sample period into three subsamples: the pre-crisis period (2003–2007), the crisis period (2007–2012), and the post-crisis period (2013–2017). The crisis period includes two devastating events of the global financial crisis and the European debt crisis during which the US stock market experienced much higher volatility than during other two periods. Thus comparing the results between the crisis and the two tranquil periods gives us useful information on how large the estimation bias for a stock-currency relationship is in times of financial turmoil.

The remainder of the paper proceeds as follows. In Section 2 we introduce the vine copula approach. In Section 3 we describe the data and report the results. Section 4 concludes.

2 Empirical methodology

2.1 Vine copula

Consider a vector of three random variables $X = (X_1, X_2, X_3)'$ with a joint distribution $F(x_1, x_2, x_3)$ and respective marginal distributions $F_1(x_1)$, $F_2(x_2)$, and $F_3(x_3)$, where $x = (x_1, x_2, x_3)'$ is a vector of realizations. In our application, X_1, X_2, and X_3 denote the US stock returns and a local country's stock and currency returns, respectively. According to the

Sklar's theorem, the joint distribution can be expressed as

$$F(x_1, x_2, x_3) = C\left(F_1(x_1), F_2(x_2), F_3(x_3)\right), \tag{1}$$

where $C : [0,1]^3 \to [0,1]$ is a copula function.[2] The copula can also be written as

$$C(u_1, u_2, u_3) = F\left(F_1^{-1}(u_1), F_2^{-1}(u_2), F_3^{-1}(u_3)\right), \tag{2}$$

where the $F_i^{-1}(u_i)$'s are inverse distribution functions of the margins. Thus the copula function can be considered a joint distribution function of $U_1 = F_1(X_1)$, $U_2 = F_2(X_2)$, and $U_3 = F_1(X_3)$, that is, $C(u_1, u_2, u_3) = \Pr(U_1 \leq u_1, U_2 \leq u_2, U_3 \leq u_3)$, where the U_i's are shown to follow a standard uniform distribution, $U_i \sim U(0,1)$, from probability integral transformation.

The probability density function of X is obtained by taking the third-order cross-partial derivative of Eq.(1):

$$f(x_1, x_2, x_3) = f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \cdot c\left(F_1(x_1), F_2(x_2), F_3(x_3)\right), \tag{3}$$

where c denotes the copula density function:

$$c\left(F_1(x_1), F_2(x_2), F_3(x_3)\right) = \frac{\partial^3 C\left(F_1(x_1), F_2(x_2), F_3(x_3)\right)}{\partial F_1(x_1) \partial F_2(x_2) \partial F_3(x_3)} = \frac{\partial^3 C(u_1, u_2, u_3)}{\partial u_1 \partial u_2 \partial u_3}. \tag{4}$$

From Eqs.(3) and (4), we can see that the copula describes the dependence structure between the variables, being completely separate from their marginal distributions.

A difficult problem in treating multivariate copulas is that while the list of bivariate copulas is long and varied, the set of higher-dimensional copulas is very limited. To overcome this problem, the vine copula approach is proposed by Joe (1996) and further investigated by, among others, Bedford and Cooke (2001, 2002), Kurowicka and Cooke (2006), and Aas et al.

[2] See Joe (1997, 2015) and Nelsen (2006) for a comprehensive exposition of copulas.

(2009). This approach decomposes a multivariate joint density into respective margins and a set of bivariate copulas, thus enabling us to construct many different forms of multivariate distributions.[3]

More specifically, in the case of our three-dimensional system, a vine representation of Eq.(3) is

$$\begin{aligned} f(x_1, x_2, x_3) &= f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \\ &\cdot c_{12}\left(F_1(x_1), F_2(x_2)\right) \cdot c_{13}\left(F_1(x_1), F_3(x_3)\right) \\ &\cdot c_{23|1}\left(F_{2|1}(x_2|x_1), F_{3|1}(x_3|x_1)\right), \end{aligned} \tag{5}$$

where c_{ij} is a bivariate copula density for the pair of transformed variables $F_i(x_i)$ and $F_j(x_j)$, and $c_{23|1}$ is a conditional copula density with two arguments defined by

$$F_{i|j}(x_i|x_j) = \frac{\partial C_{ij}\left(F_i(x_i), F_j(x_j)\right)}{\partial F_j(x_j)} = \frac{\partial C_{ij}\left(u_i, u_j\right)}{\partial u_j}. \tag{6}$$

In our application, the conditional copula $c_{23|1}$ is the most important component in Eq.(5) since it characterizes the dependence structure between a local country's stock returns (X_2) and currency returns (X_3), conditional on the values of the US stock returns (X_1).[4]

The parameters of marginal models and bivariate copulas are estimated through maximum likelihood (ML) estimation. The log-likelihood of Eq.(5) is given by

$$\begin{aligned} l(\theta^m, \theta^c; \mathbf{x}) &= \sum_{i=1}^{3}\sum_{t=1}^{T} \log f_i(x_{it}; \theta_i^m) \\ &+ \sum_{t=1}^{T} c_{12}\left(F_1(x_{1t}; \theta_1^m), F_2(x_{2t}; \theta_2^m); \theta_{12}^c\right) + \sum_{t=1}^{T} c_{13}\left(F_1(x_{1t}; \theta_1^m), F_3(x_{3t}; \theta_3^m); \theta_{13}^c\right) \\ &+ \sum_{t=1}^{T} c_{23|1}\left(F_{2|1}(x_{2t}|x_{1t}; \theta_1^m, \theta_2^m, \theta_{12}^c), F_{3|1}(x_{3t}|x_{1t}; \theta_1^m, \theta_3^m, \theta_{13}^c); \theta_{23|1}^c\right), \end{aligned} \tag{7}$$

[3] See Kurowicka and Joe (2011) for an overview and summarizing results of the vine copula approach.

[4] Aas et al. (2009) popularize two classes of vines, namely, canonical vines (C-vines) and drawable vines (D-vines), which are more tractable than the general class of vines called regular vines (R-vines). But, in the case of a three-dimensional vine, both C- and D-vines have the same expression, see Aas et al. (2009).

where $\theta^m = ((\theta_1^m)', (\theta_2^m)', (\theta_3^m)')'$ denotes a vector of parameters in three marginal models, $\theta^c = ((\theta_{12}^c)', (\theta_{13}^c)', (\theta_{23|1}^c)')$ a vector of parameters in three bivariate copulas, and $\mathbf{x} = (x_1, ..., x_T)$ where $x_t = (x_{1t}, x_{2t}, x_{3t})'$ are all observations. Because of computationally difficulty in jointly estimating all the parameters by ML, we rely on a sequential estimation procedure that has often been used in the literature applying a vine copula approach to financial data (e.g., Reboredo and Ugolini, 2015a,b). First, we estimate the parameters of each of marginal models separately. Second, given pseudo-sample observations for copula, $\hat{u}_i$ for $i = 1, 2, 3$, we estimate the parameters of each of unconditional bivariate copulas in the first tree of the vine copula structure (corresponding to the second line in Eq.(7)). Finally, given pseudo-sample observations, $\hat{F}_{2|1}$ and $\hat{F}_{3|1}$, which are obtained by using Eq.(6), we estimate the parameters of a conditional bivariate copula in the second tree of the vine copula structure (corresponding to the last line in Eq.(7)).

2.2 Specifications of marginal models and bivariate copulas

We next need to specify both marginal models and bivariate copulas in Eq.(5). In this study, marginal distributions are characterized by an ARMA(p,q)–GJR–GARCH(1,1) model with a disturbance term following the normal, Student's t, or skewed t distribution:

$$X_{it} = \alpha + \sum_{l=1}^{p} \beta_l X_{i,t-l} + \sum_{l=1}^{q} \gamma_l \varepsilon_{i,t-l} + \varepsilon_{it}, \tag{8}$$

$$\varepsilon_{it} = \sigma_{it}\eta_{it}, \tag{9}$$

$$\sigma_{it}^2 = \omega_0 + \omega_1 \sigma_{i,t-1}^2 + \omega_2 \varepsilon_{i,t-1}^2 + \tilde{\omega}_2 D_{i,t-1} \varepsilon_{i,t-1}^2, \tag{10}$$

for $i = 1, 2, 3$ and $t = 1, ..., T$. The ARMA model (8) and the GARCH model (10) represent conditional mean and conditional variance of the marginal distribution of X_{it}, respectively. The so-called GJR term, suggested by Glosten et al. (1993), appears in the last of the right-hand side of Eq.(10), where the dummy variable $D_{i,t-l}$ takes the value of 1 if $\varepsilon_{i,t-l}$ is negative and 0 otherwise. Hence the coefficient on the GJR term quantifies the leverage effect, namely, the effect that a negative shock to financial returns causes higher volatility of the returns in the future than a positive shock does. It is assumed that the standardized disturbance η_{it} in Eq.(9) is a variable that follows an independently and identically distributed (i.i.d.) normal, Student's t, or skewed t distribution. The degrees of freedom parameter ν of the Student's t distribution controls thickness of the tails, which enables us to describe well-known fat tails of financial return data. The skewed t distribution proposed by Hansen (1994) characterizes asymmetry by a skewness parameter $\zeta \in (-1, 1)$ as well as fat tails by a degrees of freedom parameter ν. It reduces to the Student's t distribution when $\zeta = 0$, to the skewed normal distribution when $\nu \to \infty$, and to the normal distribution when $\zeta = 0$ and $\nu \to \infty$. The best marginal model for each series is selected according to the Akaike information criterion (AIC).

For three kinds of bivariate copulas that constitute our vine copula structure, i.e., C_{12}, C_{13}, and $C_{23|1}$, we consider eight different forms of copula functions: Gaussian, Student's t, Clayton, Gumbel, BB7, Clayton rotated by 90 degrees, Gumbel rotated by 90 degrees, and BB7 rotated by 90 degrees. The second column in Table 1 presents functional forms of the first five copulas, followed by corresponding functions of Kendall's τ and of the lower and upper tail dependence, which are all defined as a function of copula parameter. While Kendall's τ is a measure of rank correlation indicating the average dependence between two variables of interest, the lower (upper) tail dependence means the probability that the two variables jointly take extreme negative (positive) values. As the last two columns in Table 1 show, the five copulas have different structures of tail dependence: Gaussian copula has no tail dependence; Student's t copula has the same degree of lower and upper tail dependence; Clayton copula has only lower tail dependence; Gumbel copula has only upper tail dependence; and BB7 copula has both upper and lower tail dependence, which are allowed to be different. Whereas Gaussian and Student's t copulas are able to describe both positive and negative dependence between two variables, Clayton, Gumbel, and BB7 copulas only model positive dependence. Therefore, we additionally estimate the 90-degree rotated versions of these three copulas to consider negative dependence. As in the selection of the best marginal model, we use AIC to choose the best copula model for each of the three kinds of bivariate copulas.

[Table 1 around here]

3 Data and results

3.1 Data

We analyze dependence structures between stock and currency markets by applying the vine copula approach to the following 22 developed and emerging economies: Australia, Brazil, Chile, Colombia, Czech Republic, Euro area, Hungary, India, Indonesia, Japan, Korea, Mexico, New Zealand, Norway, Philippines, Poland, South Africa, Sweden, Switzerland, Taiwan, Turkey, and the UK.[5] For each economy, our data set consists of three variables, namely, stock and currency returns of the economy and the US stock returns. We use weekly data of the MSCI stock market indices and the WM/Reuters exchange rates, both sourced from Datastream. The use of weekly frequency data is appropriate for our analysis, since it avoids the problem arising from time zone differences between the US and each of local economies as well as the problem related to drifts and noises that would be present in daily or high-frequency data. The exchange rate is expressed as the amount of units of the US dollar per local currency, implying that an increase in the exchange rate means an appreciation in the local economy's currency. We calculate time series of the three returns, that is, the US stock returns (X_{1t}), a local economy's stock returns (X_{2t}), and its currency returns (X_{3t}), as 100 times the log-difference of respective level variables.

Our full sample period spans from May 2, 2003 to September 29, 2017. The start of the sample is chosen so as not to include relatively volatile periods of the early 2000s in which the

[5]Although our data set initially includes Canada and Thailand, all of the estimated marginal models for currency returns of these two countries fail to pass the specification tests introduced in Subsection 3.2. For this reason, we exclude the two countries from our data set. Our study also excludes other large- and medium-scale economies because their exchange rate systems are not a floating one during a part or the whole of our sample period.

crash of the dot-com bubble and the 9/11 attacks occurred in the US. As will be discussed in detail in Subsection 3.3, our full sample is divided into three subsample periods in the estimation of vine copula models, according to volatility levels of the US stock returns: the pre-crisis period (May 2003 to July 2007), the crisis period (August 2007 to December 2012), and the post-crisis period (January 2013 to September 2017).

Table 2 presents descriptive statistics of the return data used in this study. Stock returns in all economies have positive means but negative skewness (except for South Africa), a negative skewness meaning a long tail in the negative direction. Further, standard deviations of the stock returns are larger than those of currency returns, showing higher risk in the stock markets. Skewness, kurtosis, and Jarque–Bera test statistics imply that the use of normal distribution might not be appropriate for modeling conditional marginal distributions of both stock and currency returns, supporting the use of Student's t and skewed t distributions in addition to the normal distribution.

[Table 2 around here]

3.2 Results for marginal models

We first estimate several variants of the marginal models for each of our return series data and select its best marginal model. More specifically, the following procedure is taken to select the best marginal model. First, we estimate several ARMA(p,q)–GJR–GARCH(1,1) models (8)–(10) that vary in three aspects: (1) those models with different order sets (p,q) of the ARMA model, each of the two lag length parameters taking the value of 0 or 1; (2) those models with and without the GJR term; (3) those models with three distinct distributions (standard normal, Student's t, and skewed t distributions) for the standardized disturbance. As a result, we estimate a total of 24 marginal models for each of our return series data. Second, a candidate for the best marginal model is chosen according to AIC. Third, we implement four diagnostic tests for that candidate: the Ljung–Box serial correlation test applied to standardized residuals $\hat{\eta}_{it}$, the same test applied to squared standardized residuals

$\hat{\eta}_{it}^2$ (setting the lag length of the two tests equal to 12 weeks), and the Kolmogorov–Smirnov and Anderson–Darling goodness-of-fit tests applied to the probability integral transforms of standardized residuals $\hat{u}_{it}$. If the candidate model is well specified, $\hat{\eta}_{it}$ and $\hat{\eta}_{it}^2$ would exhibit no serial correlation and $\hat{u}_{it}$ would be generated from an i.i.d. uniform $(0, 1)$ distribution. Thus, if it passes all of the four tests at the 5% significance level, we regard it as the best marginal model that is correctly specified. If it fails any of the four tests, we return to and repeat the second and third steps until obtaining the best marginal model.

Tables 3 and 4 report results on the best marginal models for stock returns (including the US stock return) and currency returns, respectively.[6] All of the return data except for the Swedish currency return are specified by either the Student's t distribution or the skewed t distribution. The estimate of the degrees of freedom parameter is statistically significant in most of the return series, confirming fat tail features of stock and currency returns. The skewness parameter of the skewed t distribution is estimated to be negative and statistically significant in almost all of the return series, which means that while the mode of the conditional probability density is positive, the probability of taking negative returns is larger than the probability of taking positive returns. The coefficient on the GJR term is significantly positive only for six stock and two currency returns, suggesting that the leverage effect is present in a limited number of economies, especially for currency returns. Finally, from p-values of four diagnostic tests reported in the last four columns, we confirm that all the marginal models are correctly specified, although this is obvious from our procedure of selecting the best marginal model.

[Tables 3 & 4 around here]

3.3 Results for vine copulas

We next estimate the three-variate vine copula model for each economy by which the dependence structure among a local economy's stock and currency returns and the US stock

[6]To save space, we do not report estimates of the ARMA and GARCH coefficients, which are likely to be less informative.

returns is characterized. In this estimation, we allow for structural changes in the copula parameters, because the dependence structure might vary in times of financial turbulence due to stronger co-movement among international stock markets. More precisely, it is expected that the US stock market is more closely connected to both stock and currency markets in a local economy during a financially stressful period, which would increase the estimation bias for the relationship between domestic stock and currency returns.

We allow for such structural breaks by dividing our full sample period into three subsamples: the pre-crisis period (May 2003 to July 2007), the crisis period (August 2007 to December 2012), and the post-crisis period (January 2013 to September 2017). Here the crisis period contains episodes of the global financial crisis and the subsequent European debt crisis, with the start of the period, August 2007, corresponding to BNP Paribas's announcement regarding the US securitization market. We select December 2012 as the end of the crisis period according to the US stock market volatility. Figure 1 plots a time series of the US stock market volatility, computed from the marginal model of the US stock returns estimated in the previous subsection. It is found that large fluctuations in the US stock returns, beginning from the middle of 2007 and reaching a peak in October 2008, cease at the end of 2012. It is also found that the US stock market is relatively stable in the pre- and post-crisis periods except around 2016.

[Figure 1 around here]

In what follows, we first present results from the first tree of the vine copula construction in which two kinds of relationships, that is, relationships between the US stock returns and each of a local economy's stock and currency returns are characterized. Then we provide results from the second tree of the vine copula construction where domestic stock and currency markets are connected conditional on the US stock returns.

3.3.1 Dependence structures between US and local economies' markets

Table 5 reports estimates of the Kendall's τ rank correlation between the US stock returns and each of local economies' stock returns for three subsample periods, where the Kendall's τ is computed from the estimated parameter(s) of the best bivariate copula.[7] They are all positive and statistically significant at the 1% level, providing strong evidence on the co-movement of international stock markets. In particular, the interdependence during the crisis period is largest among three periods for all of the economies except for Japan and Switzerland, implying the presence of contagion effects between international stock markets in the period.[8]

[Table 5 around here]

Table 6 presents estimates of the Kendall's τ correlation between the US stock returns and each of local economies' currency returns. Note first that in the crisis period, they are all positive and statistically significant at the 1% level, except for Japan and Switzerland. Moreover, they are greater than in any other two periods, except for Brazil. Hence, combining these results with the results from Table 5 above shows that local economies' stock returns denominated in dollars were highly positively correlated with the US stock returns during the crisis period.

[Table 6 around here]

As already noted above, however, the Japanese yen and the Swiss franc have an exceptional relationship with the US stock market. Fatum and Yamamoto (2016), Hossfeld and MacDonald (2015), Ranaldo and Söderlind (2010), and Tachibana (2017) show that international investors have regarded either or both of the two currencies as safe-haven and/or hedge currency.[9] In particular, Tachibana (2017) allows for different patterns of safe-haven and hedge behavior across three major stock markets (US, UK, and Euro area stock markets) and find that the Japanese yen has become the most important currency both as a safe-haven and

[7] To save space we do not report estimates of the copula parameters.

[8] See articles cited in the Introduction for evidence on the contagion effect during the global financial crisis.

[9] A safe-haven currency is defined as one that appreciates in times of market stress or turmoil, while a hedge currency is defined as one that is negatively correlated with another asset in normal times.

as a hedge for the US stock market since the 2007 global financial crisis. The same evidence is obtained in this study: A finding that Kendall's τ correlation between the US stock and Japanese yen returns is significantly negative in last two periods means that the Japanese yen has served as a hedge currency for the US stock market. Furthermore, the 90-degree rotated Gumbel is selected as the best copula for the two periods, supporting evidence that the Japanese yen has been a safe-haven currency for the US stock market, since that copula implies that higher probability is assigned to the region of large negative returns on the US stock market and large positive returns on the Japanese yen. The Swiss franc, on the other hand, qualifies merely as a hedge currency for the US stock market in the post-crisis period, because Kendall's τ correlation between the US stock and Swiss franc returns is significantly negative in that period, but because Gaussian copula, which has no tail dependence, is selected as the best copula. This result on the Swiss franc is again the same as the one in Tachibana (2017).

3.3.2 Dependence structures between domestic stock and currency markets conditional on the US stock returns

Here we report results regarding the main subject of our analysis: the dependence structure between domestic stock and currency markets conditional on the US stock returns. Table 7 presents the estimate of Kendall's τ rank correlation between stock and currency returns for each economy and period, which measures the conditional correlation given the values of the US stock returns and is computed from the estimated parameter(s) of the best bivariate copula in the second tree of the vine copula structure. For comparison, Table 8 presents results from the non-vine bivariate copula model that consists of only two variables of stock and currency returns, along with the differences between two estimates of Kendall's τ from the vine and non-vine models.

[Tables 7 & 8 around here]

First, controlling for the impact of the US stock market is meaningful especially for the crisis period. The differences in Kendall's τ reported in Table 8 show that correlation between domestic stock and currency returns decreases in almost all of the economies over three subsample periods when incorporating the US stock returns into the copula model. In addition, the decrease is statistically significant in 17 out of 22 economies during the crisis period, with an average change of -0.1 across all economies (which is reported in the last row of Table 8). This result suggests that upward bias is present for the crisis period when omitting the US stock returns from our copula model. It is attributable to higher correlations between the US stock returns and each of local economies' stock and currency returns during the crisis period, as already shown in Tables 5 and 6 above. For the pre- and post-crisis periods, on the other hand, there are a relatively small number of economies that have a statistically significant difference in Kendall's τ, implying that estimation bias owing to the omission of the US stock returns is limited in such tranquil periods.

Second, it is found from Table 7 that *positive* relationship between stock and currency markets is concentrated in emerging economies. The estimate of Kendall's τ is positive and statistically significant throughout three subsample periods in Brazil, Colombia, Hungary, India, Indonesia, Korea, Philippines, Poland, Taiwan, and Turkey. The positive relation is predictable both from the portfolio-balance model and from the international-trading model for an import-dominant country. The latter model, however, seems to contradict the data on trade balance given in Table 9.[10] Among the above-mentioned economies, Brazil, Hungary, Indonesia, and Korea are trade-surplus countries, which would have *negative* relationships between stock and currency returns if such export-dominant countries were affected by the international-trading effect. The portfolio-balance model, on the other hand, only predicts positive correlations regardless of international trade structure. Hence we can state that the portfolio-balance model is a more plausible theory than the international-trading model to explain positive correlations in the emerging economies. The finding on the dominance of the portfolio-balance effect in emerging economies is consistent with the results of previous

[10]The source of the data is World Development Indicators, the World Bank. Taiwan is excluded from the table due to unavailability of the data.

studies (Chkili and Nguyen, 2014; Diamandis and Drakos, 2011; Kubo, 2012; Lee et al., 2011; Phylaktis and Ravazzolo, 2005; Tsai, 2012; Reboredo et al. 2016; and Yang et al., 2014).

[Table 9 around here]

Third, in contrast to the result above, advanced economies tend to have *negative* correlations between stock and currency returns. In Euro area, Japan, Sweden, and the UK, the estimate of Kendall's τ is negative and statistically significant during two out of three subsample periods, while in Switzerland negative relationship lasts over the whole of the three periods. These results imply that the international-trading effect surpasses the portfolio-balance effect in the five advanced economies, confirming the results of Alagidede et al. (2010), Inci and Lee (2014), Kollias et al. (2012), and Tsagkanos and Siriopoulos (2013), where they all find the international-trading effect in developed economies. One caveat of our result is that among the five developed economies above, only the UK is a net import country as seen from Table 9. This might imply that at least for advanced economies, the international-trading model always predicts negative relationships regardless of trade surplus or deficit.

Even in advanced economies, however, there are cases where the international-trading effect is overtaken by the portfolio-balance effect: the sign of the Kendall's τ turns to be positive in the Euro area, Sweden, and the UK during the crisis period. This corroborates the finding of Kollias et al. (2012) and Tsagkanos and Siriopoulos (2013) that the portfolio-balance effect emerged in the European Union during the recent crisis period (2008 in Kollias et al. (2012) and 2008–2012 in Tsagkanos and Siriopoulos (2013)) whereas the international-trading effect mainly worked during the pre-crisis period.

Finally, we compare tail dependence measures between the vine and the bivariate copula models. Tables 10 and 11 report estimates of the lower and upper tail dependence, respectively, between two variables of stock and currency returns in local economies. Estimating the vine copula model with the US stock returns decreases both measures of tail dependence in most of the economy-period pairs. Further, the average decline, which is shown in each last row of the two tables, is larger during the crisis period than during pre- and post-crisis periods. Note, however, that even in the crisis period only a few economy-period pairs exhibit a statistically significant decline in each tail dependence. This result differs from the one on the Kendall's τ correlation discussed above, where we found significant declines for most economies during the crisis period. Therefore, we conclude that controlling for the effect of the US stock market on the domestic stock-currency relationship is important both for volatile periods and for average dependence measures such as Kendall's τ, but less important for tranquil periods and for tail dependence measures.

[Tables 10 & 11 around here]

4 Conclusion

Ignoring the co-movement of international stock markets might lead to a biased estimate for the relationship between domestic stock and currency markets. This paper uses the US stock returns as a proxy for the movement of foreign stock markets and applies a vine copula approach to 22 economies over the period 2003–2017. Our most concern in this analysis is whether the bias becomes larger in times of financial turbulence than in normal times, since local economies' stock and currency markets might be more highly correlated with the US stock market during the volatile times. To allow for this possibility, we divide our entire sample period into three subsamples, one of which is the crisis period of 2007–2012 that includes two recent episodes of financial crises.

We find several interesting results. First, the interdependence between the US stock market and each of local economies' stock and currency markets had been intensified during the crisis period. Second, as a result, Kendall's τ correlation between domestic stock and currency returns significantly decreases in most of the economies for the crisis period, compared with the one estimated from the non-vine bivariate model without the US stock returns. This suggests that estimation bias for the stock-currency relationship is not negligible particularly in times of financial turmoil and that it is meaningful to consider the effect of the US or foreign stock markets on the relationship to correct the bias. Third, correlation between domestic stock and currency returns tends to be positive in emerging economies, which is consistent with the portfolio-balance model, whereas it tends to be negative in developed economies, which is explained by the international-trading model. However, the sign of the correlation in European developed economies turns to be positive in the crisis period, meaning that relative strength between the portfolio-balance effect and the international-trading effect can vary depending on market conditions. Finally, we obtain only weak evidence on the presence of the bias for the lower and upper tail dependence. Therefore, we conclude that controlling for the effect of the US stock market on the domestic stock-currency relationship is important both for volatile periods and for average dependence measures such as Kendall's τ, but less important for tranquil periods and for tail dependence measures.

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References

[1] Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-Copula Constructions of Multiple Dependence. *Insurance: Mathematics and Economics, 44*, 182-198.

[2] Alagidede, P., Panagiotidis, T., & Zhang, X. (2010). Causal Relationship between Stock Prices and Exchange Rates. *Journal of International Trade and Economic Development, 20*, 67–86.

[3] Aloui, R., Ben Aïssa, M.S., & Nguyen, D.K. (2011). Global Financial Crisis, Extreme Interdependences, and Contagion Effects: The Role of Economic Structure? *Journal of Banking and Finance, 35*, 130–141.

[4] Ang, A., & Bekaert, G. (2002). International Asset Allocation with Regime Shifts. *Review of Financial Studies, 15*, 1137–1187.

[5] Bahmani-Oskooee, M., & Saha, S. (2015). On the Relation between Stock Prices and Exchange Rates: A Review Article. *Journal of Economic Studies, 42*, 707–732.

[6] Bedford, T., & Cooke R.M. (2001). Probability Density Decomposition for Conditionally Dependent Random Variables Modeled by Vines. *Annals of Mathematics and Artificial Intelligence, 32*, 245–268.

[7] Bedford, T., & Cooke R.M. (2002). Vines–A New Graphical Model for Dependent Random Variables *The Annals of Statistics, 30*, 1031–1068.

[8] Bekiros, S.D. (2014). Contagion, Decoupling and the Spillover Effects of the US Financial Crisis: Evidence from the BRIC Markets. *International Review of Financial Analysis, 33*, 58–69.

[9] Branson, W.H. (1983). Macroeconomic Determinants of Real Exchange Rate Risk. In: Herring, R.J. (Ed.), Managing Foreign Exchange Rate Risk. Cambridge University Press.

[10] Chkili, W. & Nguyen, D.K. (2014). Exchange Rate Movements and Stock Market Returns in a Regime-Switching Environment: Evidence for BRICS Countries. *Research in International Business and Finance, 31*, 46–56.

[11] Diamandis, P.F., & Drakos, A.A. (2011). Financial Liberalization, Exchange Rates and Stock Prices: Exogenous Shocks in Four Latin America Countries. *Journal of Policy Modeling, 33*, 381–394.

[12] Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global Financial Crisis and Emerging Stock Market Contagion: A Multivariate FIAPARCH-DCC Approach. *International Review of Financial Analysis, 30*, 46–56.

[13] Dornbusch, R., & Fischer, S. (1980). Exchange Rates and the Current Account. *American Economic Review, 70*, 960–971.

[14] Erb, C.B., Harvey, C.R., & Viskanta, T.E. (1994). Forecasting International Equity Correlations. *Financial Analysts Journal, 50*, 32–45.

[15] Fatum, R., & Yamamoto, Y. (2016). Intra-safe Haven Currency Behavior during the Global Financial Crisis. *Journal of International Money and Finance, 66*, 49–64.

[16] Forbes, K., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *Journal of Finance, 5*, 2223-2261.

[17] Frankel, J.A. (1983). Monetary and Portfolio-Balance Models of Exchange Rate Determination. In: Bhandari, J.S., & Putnam, B.H. (Eds.), Economic Interdependence and Flexible Exchange Rates. MIT Press.

[18] Glosten, L.R., Jagannathan, R., & Runkle, D.E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance, 48*, 1779–1801.

[19] Hansen, B.E. (1994). Autoregressive Conditional Density Estimation. *International Economic Review, 35*, 705–730.

[20] Hossfeld, O., & MacDonald, R. (2015). Carry Funding and Safe Haven Currencies: A Threshold Regression Approach. *Journal of International Money and Finance, 59*, 185–202.

[21] Inci, A.C., & Lee, B.S. (2014). Dynamic Relations between Stock Returns and Exchange Rate Changes. *European Financial Management, 20*, 71–106.

[22] Joe, H. (1996). Families of m-Variate Distributions with Given Margins and $m(m-1)/2$ Bivariate Dependence Parameters. In: Rüschendorf, L., Schweizer, B., & Taylor, M.D. (Eds.), Distributions with Fixed Marginals and Related Topics. Institute of Mathematical Statistics, Hayward, CA.

[23] Joe, H. (1997). Multivariate Models and Dependence Concepts. Chapman & Hall/CRC.

[24] Joe, H. (2015). Dependence Modeling with Copulas. CRC Press.

[25] Karanasos, M., Yfanti, S., & Karoglou, M. (2016). Multivariate FIAPARCH Modelling of Financial Markets with Dynamic Correlations in Times of Crisis. *International Review of Financial Analysis, 45*, 332–349.

[26] Kasa, K. (1992). Common Stochastic Trends in International Stock Markets. *Journal of Monetary Economics, 29*, 95–124.

[27] Kenourgios, D., & Padhi, P. (2012). Emerging Markets and Financial Crises: Regional, Global or Isolated Shocks? *Journal of Multinational Financial Management, 22*, 24–38.

[28] Kenourgios, D., & Samitas, A. (2011). Equity Market Integration in Emerging Balkan Markets. *Research in International Business and Finance, 25*, 296–307.

[29] Kim, B.H., Kim, H., & Lee, B.S. (2015). Spillover Effects of the U.S. Financial Crisis on Financial Markets in Emerging Asian Countries. *International Review of Economics and Finance, 39*, 192-210.

[30] King, M., Sentana, E., & Wadhwani, S. (1994). Volatility and Links between National Stock Markets. *Econometrica, 62*, 901–933.

[31] Kollias, C., Mylonidis, N., & Paleologou, S.M. (2012). The Nexus between Exchange Rates and Stock Markets: Evidence from the Euro-Dollar Rate and Composite European Stock Indices Using Rolling Analysis. *Journal of Economics and Finance, 36*, 136–147.

[32] Kubo, A. (2012). The US Tech Pulse, Stock Prices, and Exchange Rate Dynamics: Evidence from Asian Developing Countries. *Journal of Asian Economics, 23*, 680–687.

[33] Kurowicka, D., & Cooke, R.M. (2006). Uncertainty Analysis with High Dimensional Dependence Modelling. Wiley.

[34] Kurowicka, D., & Joe, H. (2011). Dependence Modeling: Vine Copula Handbook. World Scientific.

[35] Lee, C.H., Doong, S.C., & Chou, P.I. (2011). Dynamic Correlation between Stock Prices and Exchange Rates. *Applied Financial Economics, 21*, 789–800.

[36] Longin, F., & Solnik, B. (1995). Is the Correlation in International Equity Returns Constant: 1960-1990? *Journal of International Money and Finance, 14*, 3-26.

[37] Longin, F., & Solnik, B. (2001). Extreme Correlation of International Equity Markets. *Journal of Finance, 2*, 649-676.

[38] Michelis, L., & Ning, C. (2010). The Dependence Structure between the Canadian Stock Market and the USD/CAD Exchange Rate: A Copula Approach. *Canadian Journal of Economics, 43*, 1016–1039.

[39] Nelsen, R.B. (2006). An Introduction to Copulas. Springer.

[40] Ning, C. (2010). Dependence Structure between the Equity Market and the Foreign Exchange Market–A Copula Approach. *Journal of International Money and Finance, 29*, 743–759.

[41] Phylaktis, K., & Ravazzolo, F. (2005). Stock Prices and Exchange Rate Dynamics. *Journal of International Money and Finance, 24*, 1031–1053.

[42] Ramchand, L., & Susmel, R. (1998). Volatility and Cross Correlation across Major Stock Markets. *Journal of Empirical Finance, 5*, 397–416.

[43] Ranaldo, A., & Söderlind, P. (2010). Safe Haven Currencies. *Review of Finance, 14*, 385–407.

[44] Reboredo, J.C., Rivera-Castro, M.A., & Ugolini, A. (2016). Downside and Upside Risk Spillovers between Exchange Rates and Stock Prices. *Journal of Banking and Finance, 62*, 76–96.

[45] Reboredo, J.C. & Ugolini, A. (2015a). A Vine-Copula Conditional Value-at-Risk Approach to Systemic Sovereign Debt Risk for the Financial Sector. *North American Journal of Economics and Finance, 32*, 98–123.

[46] Reboredo, J.C. & Ugolini, A. (2015b). Downside/Upside Price Spillovers between Precious Metals: A Vine Copula Approach. *North American Journal of Economics and Finance, 34*, 84–102.

[47] Samarakoon, L.P. (2011). Stock Market Interdependence, Contagion, and the U.S. Financial Crisis: The Case of Emerging and Frontier Markets. *Journal of International Financial Markets, Institutions and Money, 21*, 724–742.

[48] Solnik, B., Boucrelle, C., & Le Fur, Y. (1996). International Market Correlation and Volatility. *Financial Analysts Journal, 52*, 17–34.

[49] Sui, L., & Sun, L. (2016). Spillover Effects between Exchange Rates and Stock Prices: Evidence from BRICS around the Recent Global Financial Crisis. *Research in International Business and Finance, 36*, 459–471.

[50] Syllignakis, M.N., & Kouretas, G.P. (2011). Dynamic Correlation Analysis of Financial Contagion: Evidence from the Central and Eastern European Markets. *International Review of Economics and Finance, 20*, 717–732.

[51] Tachibana, M. (2017). Safe-Haven and Hedge Currencies for the US, UK, and Euro Area Stock Markets: A Copula-Based Approach. *Global Finance Journal*, in press.

[52] Tsagkanos, A., & Siriopoulos, C. (2013). A Long-Run Relationship between Stock Price Index and Exchange Rate: A Structural Nonparametric Cointegrating Regression Approach. *Journal of International Financial Markets, Institutions and Money, 25*, 106–118.

[53] Tsai, I.C. (2012). The Relationship between Stock Price Index and Exchange Rate in Asian Markets: A Quantile Regression Approach. *Journal of International Financial Markets, Institutions and Money, 22*, 609-621.

[54] Wang, Y.C., Wu, J.L., & Lai, Y.H. (2013). A Revisit to the Dependence Structure between the Stock and Foreign Exchange Markets: A Dependence-Switching Copula Approach. *Journal of Banking and Finance, 37* 1706–1719.

[55] Yang, L., & Hamori, S. (2013). Dependence Structure among International Stock Markets: A GARCH-Copula Analysis. *Applied Financial Economics, 23*, 1805–1817.

[56] Yang, Z., Tu, A.H., & Zeng, Y. (2014). Dynamic Linkages between Asian Stock Prices and Exchange Rates: New Evidence from Causality in Quantiles. *Applied Economics, 46*, 1184–1201.

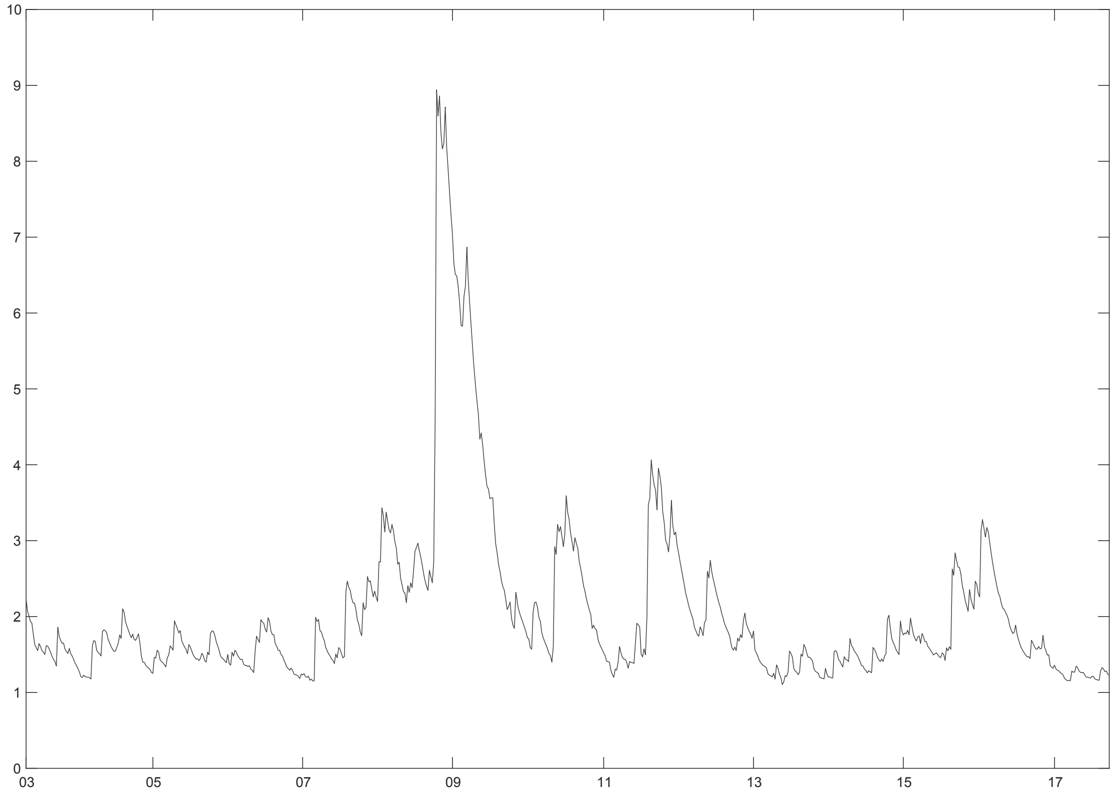

Figure 1: US stock market volatility. The figure presents a time-series plot of conditional standard deviation of the US stock returns, $\hat{\sigma}_{1t}$, which is computed from the marginal model of the US stock returns.

Table 1: Bivariate copulas constituting vine copula constructions

Name	Copula CDF	Kendall's τ	Lower tail	Upper tail
Gaussian	$C_N(u_1, u_2; \rho) = \Phi_2\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \rho\right)$	$2\pi^{-1} \arcsin(\rho)$	0	0
Student's t	$C_T(u_1, u_2; \rho, \nu) = T_{2,\nu}\left(T_\nu^{-1}(u_1), T_\nu^{-1}(u_2); \rho\right)$	$2\pi^{-1} \arcsin(\rho)$	See notes below	
Clayton	$C_C(u_1, u_2; \delta) = (u_1^{-\delta} + u_2^{-\delta} - 1)^{-1/\delta}$	$\delta/(\delta+2)$	$2^{-1/\delta}$	0
Gumbel	$C_G(u_1, u_2; \delta) = \exp\left(-\left[(-\log u_1)^\delta + (-\log u_2)^\delta\right]^{1/\delta}\right)$	$(\delta-1)/\delta$	0	$2 - 2^{1/\delta}$
BB7	$C_{BB7}(u_1, u_2; \delta, \theta) = 1 - \left(1 - \left[(1-(1-u_1)^\theta)^{-\delta} + (1-(1-u_2)^\theta)^{-\delta} - 1\right]^{-1/\delta}\right)^{1/\theta}$	See notes below	$2^{-1/\delta}$	$2 - 2^{1/\theta}$

Notes: The second column in the table presents cumulative distribution functions (CDFs) of the bivariate copulas used to construct vine copula models. Φ and Φ_2 (T_ν and $T_{2,\nu}$) denote the CDFs of the standard univariate and bivariate normal (Student's t) distributions, respectively. The third column shows functions to compute Kendall's τ. The Kendall's τ of BB7 copula is: $\tau = 1 - 2\delta^{-1}(2-\theta)^{-1} + 4\delta^{-1}\theta^{-2}B(\delta+2, 2/\theta - 1)$, where $B(\cdot,\cdot)$ denotes the beta function. The last two columns present the lower and upper tail dependence of each copula. The tail dependence of Student's t copula is: $\lambda_L = \lambda_U = 2T_{\nu+1}\left(-\sqrt{(\nu+1)(1-\rho)/(1+\rho)}\right)$. In addition to the five bivariate copulas above, we use the 90-degree rotated versions of Clayton, Gumbel, and BB7, which are defined as $C_{90}(u_1, u_2) = u_2 - C(1-u_1, u_2)$.

Table 2: Descriptive statistics

	Mean	Max	Min	SD	Skewness	Kurtosis	JB
Panel A: Stock returns							
US	0.139	11.526	-20.116	2.297	-1.027	13.409	3531.75***
Australia	0.085	9.733	-16.490	2.208	-0.900	8.684	1115.18***
Brazil	0.207	16.892	-21.357	3.468	-0.330	7.254	581.34***
Chile	0.160	16.662	-22.956	2.486	-1.010	15.702	5190.20***
Colombia	0.296	11.474	-22.037	2.983	-0.822	10.338	1774.15***
Czech Rep.	0.078	18.285	-27.484	3.039	-1.022	14.937	4601.62***
Euro area	0.087	10.820	-24.472	2.765	-1.333	12.593	3110.74***
Hungary	0.148	17.746	-35.012	3.745	-1.335	15.097	4814.71***
India	0.296	13.660	-19.000	3.079	-0.571	6.791	491.76***
Indonesia	0.342	13.012	-22.383	3.489	-0.627	7.136	586.08***
Japan	0.099	9.642	-22.318	2.869	-1.020	8.818	1192.55***
Korea	0.197	18.819	-21.403	2.956	-0.652	9.528	1390.38***
Mexico	0.255	17.217	-19.313	2.783	-0.508	10.057	1595.05***
New Zealand	0.048	7.148	-13.429	1.933	-0.671	6.835	518.07***
Norway	0.157	15.341	-24.610	3.223	-1.216	11.349	2372.69***
Philippines	0.248	12.523	-19.600	2.891	-0.591	7.571	699.22***
Poland	0.101	16.078	-16.703	3.067	-0.375	6.004	300.69***
South Africa	0.247	16.264	-9.695	2.581	0.140	6.234	330.70***
Sweden	0.172	12.603	-22.670	2.850	-0.955	10.131	1709.76***
Switzerland	0.098	12.299	-24.788	2.407	-1.872	22.321	12152.46***
Taiwan	0.100	9.448	-11.478	2.682	-0.638	4.763	148.65***
Turkey	0.193	13.482	-28.601	3.129	-1.094	13.065	3328.84***
UK	0.081	12.549	-23.430	2.368	-1.382	18.607	7881.65***
Panel B: Currency returns							
Australia	0.032	7.040	-17.805	1.867	-1.716	16.455	6049.71***
Brazil	-0.006	9.141	-12.579	2.093	-0.829	8.229	944.12***
Chile	0.014	6.527	-11.706	1.600	-0.945	9.210	1321.79***
Colombia	-0.001	9.177	-13.129	1.758	-0.674	9.224	1272.51***
Czech Rep.	0.035	6.193	-7.586	1.693	-0.444	4.009	56.69***
Euro area	0.009	5.331	-5.623	1.365	-0.301	4.073	47.51***
Hungary	-0.022	7.518	-9.992	2.082	-0.524	4.856	142.52***
India	-0.043	4.706	-4.489	0.927	-0.228	6.050	298.41***
Indonesia	-0.057	8.718	-8.543	1.097	-0.002	17.460	6559.86***
Japan	0.009	8.466	-5.421	1.449	0.370	5.076	152.40***
Korea	0.010	9.816	-6.988	1.390	0.059	10.995	2006.08***
Mexico	-0.074	5.980	-15.798	1.638	-1.613	17.274	6719.01***
New Zealand	0.036	6.716	-11.990	1.922	-0.888	6.983	596.53***
Norway	-0.015	7.009	-6.400	1.690	-0.328	3.769	32.11***
Philippines	0.006	2.642	-3.770	0.747	-0.035	4.942	118.50***
Poland	0.009	7.989	-12.923	2.011	-0.933	7.136	645.96***
South Africa	-0.083	11.337	-11.285	2.379	-0.533	5.343	207.90***
Sweden	0.002	6.537	-6.557	1.649	-0.214	4.097	43.50***
Switzerland	0.046	17.329	-12.096	1.628	1.075	23.126	12854.18***
Taiwan	0.019	2.368	-2.757	0.588	-0.054	5.144	144.65***
Turkey	0.034	5.448	-6.340	0.801	-0.341	13.574	3522.86***
UK	-0.023	5.328	-8.664	1.378	-0.762	7.294	651.23***

Notes: Weekly stock and currency returns for the period May 2, 2003 to September 29, 2017. SD denotes the standard deviation. JB is the Jarque–Bera statistics for the test of normality. *** indicates rejection of the null hypothesis of normality at the 1% level.

Table 3: Estimation results for best marginal models of stock returns

	Dist.	p	q	GJR	DoF	Skewness	$Q(12)$	$Q^2(12)$	KS	AD
US	S	1	1	0.161 *	12.127 **	-0.421 ***	[0.089]	[0.062]	[0.204]	[0.648]
				(0.083)	(5.308)	(0.050)				
Australia	S	1	1	0.132	10.703 ***	-0.325 ***	[0.492]	[0.969]	[0.357]	[0.604]
				(0.101)	(3.979)	(0.060)				
Brazil	S	0	0	0.111	11.647 ***	-0.213 ***	[0.368]	[0.898]	[0.942]	[0.912]
				(0.079)	(3.531)	(0.054)				
Chile	S	1	1	0.181 *	10.685 ***	-0.146 ***	[0.682]	[0.936]	[0.840]	[0.896]
				(0.094)	(3.408)	(0.055)				
Colombia	S	0	0		3.966 ***	-0.097 **	[0.131]	[0.984]	[0.682]	[0.801]
					(0.638)	(0.048)				
Czech Rep.	S	0	0		5.491 ***	-0.179 ***	[0.585]	[0.584]	[0.819]	[0.814]
					(1.014)	(0.053)				
Euro area	S	0	1	0.185 **	10.547 ***	-0.367 ***	[0.911]	[0.988]	[0.633]	[0.853]
				(0.080)	(2.788)	(0.054)				
Hungary	T	0	0	0.065	6.020 ***		[0.386]	[0.999]	[0.396]	[0.477]
				(0.098)	(0.870)					
India	S	0	0	0.112	15.511 **	-0.202 ***	[0.623]	[0.741]	[0.796]	[0.773]
				(0.125)	(6.478)	(0.050)				
Indonesia	S	1	0	0.148	4.682 ***	-0.073	[0.355]	[0.985]	[0.978]	[0.979]
				(0.127)	(0.913)	(0.052)				
Japan	S	0	1	0.237 **	11.609 **	-0.233 ***	[0.732]	[0.381]	[0.987]	[0.998]
				(0.096)	(5.140)	(0.051)				
Korea	S	1	1	0.127	10.739 **	-0.274 ***	[0.582]	[0.504]	[0.949]	[0.992]
				(0.084)	(4.584)	(0.053)				
Mexico	S	1	1	0.116	11.411 ***	-0.254 ***	[0.824]	[0.679]	[0.964]	[0.969]
				(0.110)	(4.154)	(0.057)				
New Zealand	S	0	0	0.061	15.708 **	-0.133 **	[0.747]	[0.464]	[0.911]	[0.953]
				(0.071)	(7.913)	(0.059)				
Norway	S	0	0	0.166	5.292 ***	-0.244 ***	[0.965]	[0.599]	[0.979]	[0.977]
				(0.101)	(1.169)	(0.050)				
Philippines	S	1	0	0.061	6.545 ***	-0.125 **	[0.926]	[0.936]	[0.907]	[0.902]
				(0.094)	(1.343)	(0.051)				
Poland	S	0	0	0.044	8.431 ***	-0.088	[0.856]	[0.904]	[0.999]	[0.989]
				(0.091)	(2.193)	(0.060)				
South Africa	S	1	0	0.150	24.451	-0.173 ***	[0.912]	[0.518]	[0.955]	[0.963]
				(0.097)	(17.254)	(0.056)				
Sweden	S	0	1	0.130	6.843 ***	-0.274 ***	[0.840]	[0.974]	[0.951]	[0.976]
				(0.100)	(1.542)	(0.052)				
Switzerland	S	0	1	0.300 **	6.220 ***	-0.300 ***	[0.889]	[1.000]	[0.535]	[0.829]
				(0.119)	(0.993)	(0.052)				
Taiwan	S	0	1	0.059	9.531 ***	-0.240 ***	[0.651]	[0.080]	[0.822]	[0.958]
				(0.099)	(3.401)	(0.053)				
Turkey	T	1	1		9.274 ***		[0.557]	[0.355]	[0.681]	[0.624]
					(3.020)					
UK	S	1	1	0.137 *	7.106 ***	-0.314 ***	[0.170]	[0.921]	[0.900]	[0.909]
				(0.082)	(1.425)	(0.054)				

Notes: The table reports results on the best marginal models of stock returns, selected from the class of ARMA(p,q)–GJR–GARCH(1,1) models. The sample period is from May 2, 2003 to September 29, 2017. The first column (Dist.) shows selected distribution functions for the standardized disturbance, where N, T, and S denote the standard normal, Student's t, and skewed t distributions, respectively. The second and third columns (p, q) present the numbers of lag length for the AR and MA terms, respectively. The fourth to sixth columns (GJR, DoF, Skewness) report estimates of the coefficient of the GJR term, estimates of the degrees of freedom parameter for the Student's t and skewed t distributions, and estimates of the skewness parameter for the skewed t distribution, respectively. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. $Q(12)$ and $Q^2(12)$ denote the Ljung–Box serial correlation tests applied to standardized residuals and squared standardized residuals, respectively, with lag length of 12 weeks. KS and AD denote the Kolmogorov–Smirnov and Anderson–Darling tests, respectively, for the adequacy of the marginal distribution. For these four tests, p-values are reported in brackets.

Table 4: Estimation results for best marginal models of currency returns

	Dist.	p	q	GJR	DoF	Skewness	$Q(12)$	$Q^2(12)$	KS	AD
Australia	S	1	1	0.091 (0.100)	8.879 *** (2.753)	-0.322 *** (0.051)	[0.091]	[0.558]	[0.610]	[0.585]
Brazil	S	0	0	0.129 (0.110)	7.344 *** (1.971)	-0.197 *** (0.053)	[0.668]	[0.940]	[0.893]	[0.958]
Chile	S	0	0		8.393 *** (2.178)	-0.132 ** (0.054)	[0.550]	[0.957]	[0.974]	[0.992]
Colombia	S	1	1		5.483 *** (1.046)	-0.162 *** (0.055)	[0.860]	[0.994]	[0.748]	[0.883]
Czech Rep.	S	0	0		38.486 (52.882)	-0.186 *** (0.059)	[0.585]	[0.636]	[0.940]	[0.992]
Euro area	S	0	0	0.049 (0.085)	54.706 (95.222)	-0.183 *** (0.058)	[0.504]	[0.441]	[0.973]	[0.986]
Hungary	S	0	0	0.054 (0.089)	17.865 ** (8.761)	-0.223 *** (0.057)	[0.851]	[0.939]	[0.955]	[0.977]
India	T	1	1	0.112 (0.133)	3.664 *** (0.664)		[0.332]	[0.881]	[0.514]	[0.561]
Indonesia	T	1	1		2.619 *** (0.317)		[0.149]	[0.862]	[0.462]	[0.622]
Japan	T	0	0		9.153 *** (2.760)		[0.289]	[0.115]	[0.995]	[0.970]
Korea	S	1	1	0.222 ** (0.113)	8.323 *** (2.193)	-0.131 ** (0.051)	[0.164]	[0.677]	[0.738]	[0.967]
Mexico	S	0	0	0.169 ** (0.086)	6.135 *** (1.091)	-0.217 *** (0.056)	[0.063]	[0.991]	[0.991]	[0.951]
New Zealand	S	0	0	0.067 (0.084)	11.074 ** (4.343)	-0.297 *** (0.052)	[0.821]	[0.388]	[0.665]	[0.970]
Norway	S	0	0	0.061 (0.081)	23.507 (15.930)	-0.252 *** (0.055)	[0.909]	[0.997]	[0.993]	[0.999]
Philippines	T	0	0		6.112 *** (1.849)		[0.116]	[0.958]	[0.956]	[0.932]
Poland	S	0	0		11.137 *** (3.737)	-0.250 *** (0.055)	[0.391]	[0.973]	[0.682]	[0.954]
South Africa	S	0	1	0.040 (0.085)	12.252 *** (4.621)	-0.314 *** (0.054)	[0.263]	[0.998]	[0.981]	[0.956]
Sweden	N	0	0	0.057 (0.086)			[0.950]	[0.705]	[0.221]	[0.474]
Switzerland	T	0	0		8.229 *** (0.956)		[0.493]	[1.000]	[0.397]	[0.290]
Taiwan	T	1	0		4.868 *** (1.183)		[0.110]	[0.660]	[0.491]	[0.501]
Turkey	S	0	0	0.141 (0.093)	7.747 *** (2.433)	-0.226 *** (0.055)	[0.671]	[0.589]	[0.682]	[0.577]
UK	S	1	1	0.073 (0.075)	28.273 (26.168)	-0.222 *** (0.058)	[0.813]	[0.807]	[0.078]	[0.277]

Notes: The table reports results on the best marginal models of currency returns. See also notes in Table 3.

Table 5: Estimation results for vine copulas (first tree): dependence between US and local economies' stock returns

	Pre-crisis period		Crisis period		Post-crisis period	
	Copula	Kendall's τ	Copula	Kendall's τ	Copula	Kendall's τ
Australia	Clayton	0.297 ***	BB7	0.411 ***	Gaussian	0.399 ***
		(0.032)		(0.024)		(0.031)
Brazil	Student's t	0.456 ***	Student's t	0.500 ***	Gaussian	0.275 ***
		(0.036)		(0.029)		(0.032)
Chile	Gaussian	0.244 ***	Gaussian	0.329 ***	Clayton	0.251 ***
		(0.036)		(0.028)		(0.032)
Colombia	BB7	0.211 ***	BB7	0.239 ***	Clayton	0.156 ***
		(0.041)		(0.032)		(0.035)
Czech Rep.	Clayton	0.229 ***	Gaussian	0.285 ***	Gaussian	0.218 ***
		(0.035)		(0.032)		(0.041)
Euro area	Gaussian	0.572 ***	Student's t	0.650 ***	BB7	0.445 ***
		(0.020)		(0.019)		(0.025)
Hungary	Gaussian	0.273 ***	Gaussian	0.376 ***	Gaussian	0.178 ***
		(0.037)		(0.026)		(0.044)
India	Gaussian	0.285 ***	BB7	0.327 ***	Gaussian	0.307 ***
		(0.032)		(0.026)		(0.032)
Indonesia	Gaussian	0.227 ***	Gaussian	0.273 ***	Clayton	0.124 ***
		(0.034)		(0.032)		(0.039)
Japan	Clayton	0.336 ***	Clayton	0.327 ***	Gaussian	0.402 ***
		(0.037)		(0.025)		(0.028)
Korea	Clayton	0.289 ***	Student's t	0.384 ***	Clayton	0.264 ***
		(0.032)		(0.034)		(0.034)
Mexico	BB7	0.437 ***	Student's t	0.532 ***	BB7	0.338 ***
		(0.029)		(0.026)		(0.030)
New Zealand	Gaussian	0.136 ***	Student's t	0.278 ***	Student's t	0.143 ***
		(0.043)		(0.039)		(0.047)
Norway	Clayton	0.303 ***	Gaussian	0.502 ***	Student's t	0.423 ***
		(0.030)		(0.020)		(0.038)
Philippines	Clayton	0.242 ***	Gaussian	0.256 ***	Gaussian	0.230 ***
		(0.031)		(0.032)		(0.037)
Poland	Gaussian	0.297 ***	Student's t	0.388 ***	Gaussian	0.314 ***
		(0.038)		(0.032)		(0.035)
South Africa	Gaussian	0.348 ***	Gaussian	0.395 ***	Gaussian	0.320 ***
		(0.032)		(0.026)		(0.033)
Sweden	BB7	0.432 ***	Student's t	0.551 ***	Student's t	0.493 ***
		(0.027)		(0.025)		(0.033)
Switzerland	Student's t	0.496 ***	BB7	0.470 ***	Gaussian	0.499 ***
		(0.033)		(0.022)		(0.025)
Taiwan	BB7	0.265 ***	Student's t	0.332 ***	Clayton	0.279 ***
		(0.037)		(0.037)		(0.032)
Turkey	Clayton	0.164 ***	Clayton	0.278 ***	Gaussian	0.247 ***
		(0.036)		(0.025)		(0.035)
UK	BB7	0.479 ***	Student's t	0.655 ***	BB7	0.468 ***
		(0.029)		(0.018)		(0.025)

Notes: The table reports estimates of the Kendall's τ correlation between the US stock returns and each of local economies' stock returns, computed from the first tree of the three-variate vine copula construction. The pre-crisis period is from May 2, 2003 to July 27, 2007; the crisis period is from August 3, 2007 to December 28, 2012; and the post-crisis period is from January 4, 2013 to September 29, 2017. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Estimation results for vine copulas (first tree): dependence between US stock and local economies' currency returns

	Pre-crisis period		Crisis period		Post-crisis period	
	Copula	Kendall's τ	Copula	Kendall's τ	Copula	Kendall's τ
Australia	Clayton	0.161 ***	BB7	0.354 ***	Clayton	0.129 ***
		(0.037)		(0.027)		(0.038)
Brazil	Gaussian	0.298 ***	BB7	0.296 ***	Clayton	0.141 ***
		(0.039)		(0.031)		(0.032)
Chile	Clayton	0.223 ***	Student's t	0.261 ***	Gaussian	0.157 ***
		(0.033)		(0.039)		(0.039)
Colombia	Clayton	0.175 ***	Gaussian	0.211 ***	Clayton	0.182 ***
		(0.043)		(0.034)		(0.035)
Czech Rep.	Clayton	0.115 ***	Student's t	0.197 ***	Gaussian	-0.079 *
		(0.035)		(0.041)		(0.045)
Euro area	Clayton	0.113 ***	Clayton	0.151 ***	Gaussian	-0.063
		(0.036)		(0.027)		(0.044)
Hungary	Student's t	0.157 ***	BB7	0.248 ***	Student's t	0.030
		(0.051)		(0.030)		(0.049)
India	Gaussian	0.215 ***	Gaussian	0.290 ***	Clayton	0.153 ***
		(0.041)		(0.030)		(0.030)
Indonesia	Gaussian	0.168 ***	Student's t	0.238 ***	Gaussian	0.107 ***
		(0.039)		(0.042)		(0.038)
Japan	Student's t	0.102 **	90° rotated	-0.182 ***	90° rotated	-0.260 ***
		(0.050)	Gumbel	(0.035)	Gumbel	(0.036)
Korea	Clayton	0.139 ***	Student's t	0.304 ***	Student's t	0.143 ***
		(0.041)		(0.039)		(0.050)
Mexico	Gaussian	0.226 ***	Student's t	0.409 ***	Student's t	0.238 ***
		(0.041)		(0.031)		(0.047)
New Zealand	Clayton	0.139 ***	BB7	0.291 ***	Student's t	0.042
		(0.038)		(0.028)		(0.049)
Norway	Clayton	0.082 **	BB7	0.252 ***	Gaussian	0.085 *
		(0.035)		(0.028)		(0.044)
Philippines	Clayton	0.146 ***	Gaussian	0.255 ***	Clayton	0.115 ***
		(0.040)		(0.030)		(0.038)
Poland	Gaussian	0.173 ***	Student's t	0.279 ***	Student's t	0.056
		(0.042)		(0.037)		(0.049)
South Africa	Student's t	0.108 **	Student's t	0.333 ***	Student's t	0.187 ***
		(0.052)		(0.035)		(0.048)
Sweden	Student's t	0.143 ***	BB7	0.235 ***	Gaussian	0.021
		(0.049)		(0.032)		(0.046)
Switzerland	Gumbel	0.053	Student's t	0.056	Gaussian	-0.121 ***
		(0.039)		(0.039)		(0.046)
Taiwan	BB7	0.165 ***	Gaussian	0.237 ***	Student's t	0.111 **
		(0.037)		(0.030)		(0.047)
Turkey	Gaussian	0.293 ***	Student's t	0.346 ***	Clayton	0.163 ***
		(0.038)		(0.035)		(0.032)
UK	Clayton	0.103 ***	Clayton	0.138 ***	Gaussian	0.097 **
		(0.037)		(0.027)		(0.042)

Notes: The table reports estimates of the Kendall's τ correlation between the US stock returns and each of local economies' currency returns, computed from the first tree of the three-variate vine copula construction. See also notes in Table 5.

Table 7: Estimation results for vine copulas (second tree): dependence between stock and currency returns in local economies

	Pre-crisis period		Crisis period		Post-crisis period	
	Copula	Kendall's τ	Copula	Kendall's τ	Copula	Kendall's τ
Australia	Clayton	0.058	Gaussian	0.142 ***	Gumbel	0.060
		(0.042)		(0.033)		(0.042)
Brazil	Student's t	0.194 ***	Gaussian	0.274 ***	BB7	0.258 ***
		(0.052)		(0.031)		(0.037)
Chile	Gaussian	-0.027	Clayton	0.033	Gaussian	0.145 ***
		(0.041)		(0.028)		(0.044)
Colombia	Clayton	0.091 ***	Clayton	0.055 *	Gaussian	0.218 ***
		(0.035)		(0.030)		(0.039)
Czech Rep.	Student's t	0.018	Gaussian	0.073 *	Gaussian	-0.039
		(0.048)		(0.039)		(0.045)
Euro area	90° rotated	-0.236 ***	Gaussian	0.092 **	Student's t	-0.171 ***
	Clayton	(0.029)		(0.036)		(0.047)
Hungary	Clayton	0.153 ***	Student's t	0.205 ***	Clayton	0.106 ***
		(0.037)		(0.045)		(0.037)
India	Clayton	0.174 ***	Gaussian	0.335 ***	Gaussian	0.322 ***
		(0.039)		(0.027)		(0.036)
Indonesia	Clayton	0.204 ***	Student's t	0.301 ***	BB7	0.242 ***
		(0.034)		(0.039)		(0.036)
Japan	Student's t	-0.044	90° rotated	-0.212 ***	90° rotated	-0.363 ***
		(0.052)	BB7	(0.030)	BB7	(0.030)
Korea	Gaussian	0.096 **	Gaussian	0.335 ***	Gaussian	0.249 ***
		(0.040)		(0.028)		(0.035)
Mexico	Clayton	0.013	90° rotated	-0.011	Student's t	0.160 ***
		(0.043)	Gumbel	(0.029)		(0.049)
New Zealand	Gaussian	-0.073	Student's t	-0.047	90° rotated	-0.054
		(0.045)		(0.040)	Clayton	(0.038)
Norway	90° rotated	-0.045	Gaussian	0.201 ***	Gumbel	0.049
	Clayton	(0.035)		(0.034)		(0.045)
Philippines	Gaussian	0.165 ***	Clayton	0.154 ***	Gaussian	0.241 ***
		(0.040)		(0.031)		(0.039)
Poland	Student's t	0.104 **	Gaussian	0.209 ***	Gaussian	0.159 ***
		(0.049)		(0.033)		(0.042)
South Africa	Student's t	-0.079 *	Clayton	0.158 ***	Gumbel	0.162 ***
		(0.047)		(0.030)		(0.039)
Sweden	90° rotated	-0.143 ***	Clayton	0.086 ***	90° rotated	-0.133 ***
	Clayton	(0.038)		(0.032)	Gumbel	(0.042)
Switzerland	Gaussian	-0.247 ***	Gaussian	-0.112 ***	90° rotated	-0.291 ***
		(0.040)		(0.035)	Gumbel	(0.038)
Taiwan	Gaussian	0.243 ***	Gaussian	0.274 ***	Gaussian	0.280 ***
		(0.032)		(0.032)		(0.031)
Turkey	Student's t	0.318 ***	Gaussian	0.310 ***	Student's t	0.394 ***
		(0.045)		(0.031)		(0.037)
UK	Gaussian	-0.230 ***	Clayton	0.020	Gaussian	-0.234 ***
		(0.035)		(0.027)		(0.037)

Notes: The table reports estimates of the Kendall's τ correlation between stock and currency returns in local economies, computed from the second tree of the three-variate vine copula construction. See also notes in Table 5.

Table 8: Estimation results for non-vine bivariate copulas (not including the US stock returns)

	Pre-crisis period			Crisis period			Post-crisis period		
	Copula	Kendall's τ	Difference	Copula	Kendall's τ	Difference	Copula	Kendall's τ	Difference
Australia	Clayton	0.129 ***	-0.071	BB7	0.304 ***	-0.161 ***	Gaussian	0.114 ***	-0.054
		(0.040)			(0.030)			(0.042)	
Brazil	Student's t	0.318 ***	-0.124 *	Student's t	0.413 ***	-0.139 ***	BB7	0.299 ***	-0.041
		(0.047)			(0.034)			(0.036)	
Chile	Clayton	0.130 ***	-0.157 ***	Student's t	0.148 ***	-0.115 **	Gaussian	0.201 ***	-0.056
		(0.034)			(0.041)			(0.041)	
Colombia	Clayton	0.152 ***	-0.061	Clayton	0.122 ***	-0.067	Gaussian	0.261 ***	-0.043
		(0.033)			(0.028)			(0.037)	
Czech Rep.	Student's t	0.054	-0.036	Gaussian	0.154 ***	-0.081	90° rotated	-0.068	0.029
		(0.047)			(0.036)		Gumbel	(0.046)	
Euro area	90° rotated	-0.081 **	-0.155 ***	Gaussian	0.211 ***	-0.119 **	Student's t	-0.180 ***	0.009
	Clayton	(0.038)			(0.032)			(0.049)	
Hungary	Clayton	0.171 ***	-0.018	Student's t	0.306 ***	-0.102 *	Clayton	0.125 ***	-0.019
		(0.037)			(0.037)			(0.037)	
India	Clayton	0.222 ***	-0.048	Gaussian	0.421 ***	-0.086 **	Gaussian	0.361 ***	-0.038
		(0.039)			(0.023)			(0.034)	
Indonesia	BB7	0.260 ***	-0.056	Student's t	0.357 ***	-0.056	BB7	0.259 ***	-0.018
		(0.034)			(0.037)			(0.037)	
Japan	Student's t	-0.002	-0.042	Student's t	-0.298 ***	0.087 *	Gaussian	-0.463 ***	0.100 **
		(0.054)			(0.038)			(0.025)	
Korea	Clayton	0.161 ***	-0.065	Gaussian	0.429 ***	-0.094 ***	Gaussian	0.300 ***	-0.051
		(0.034)			(0.022)			(0.034)	
Mexico	Gaussian	0.141 ***	-0.128 **	Student's t	0.308 ***	-0.319 ***	Gaussian	0.277 ***	-0.117 **
		(0.042)			(0.039)			(0.031)	
New Zealand	Gaussian	-0.043	-0.030	Clayton	0.114 ***	-0.161 ***	90° rotated	-0.036	-0.018
		(0.044)			(0.024)		Clayton	(0.035)	
Norway	Clayton	0.036	-0.081 *	Gaussian	0.326 ***	-0.125 ***	Gumbel	0.085 *	-0.035
		(0.032)			(0.030)			(0.044)	
Philippines	Clayton	0.221 ***	-0.056	BB7	0.230 ***	-0.076 *	Gaussian	0.262 ***	-0.021
		(0.037)			(0.032)			(0.039)	
Poland	BB7	0.171 ***	-0.067	Gaussian	0.325 ***	-0.115 ***	BB7	0.161 ***	-0.002
		(0.040)			(0.027)			(0.042)	
South Africa	Student's t	-0.016	-0.064	Student's t	0.327 ***	-0.169 ***	Gumbel	0.216 ***	-0.053
		(0.047)			(0.037)			(0.039)	
Sweden	Student's t	-0.042	-0.101 *	BB7	0.231 ***	-0.146 ***	Student's t	-0.079	-0.054
		(0.046)			(0.031)			(0.050)	
Switzerland	Gaussian	-0.154 ***	-0.093 *	90° rotated	-0.053 *	-0.060	90° rotated	-0.274 ***	-0.017
		(0.039)		Gumbel	(0.029)		Gumbel	(0.038)	
Taiwan	Gaussian	0.279 ***	-0.036	Gaussian	0.349 ***	-0.075 *	Student's t	0.334 ***	-0.055
		(0.032)			(0.027)			(0.042)	
Turkey	Student's t	0.369 ***	-0.051	Gaussian	0.425 ***	-0.115 ***	Student's t	0.425 ***	-0.031
		(0.043)			(0.024)			(0.036)	
UK	Gaussian	-0.079 *	-0.151 ***	Clayton	0.129 ***	-0.109 ***	Gaussian	-0.116 ***	-0.118 **
		(0.041)			(0.027)			(0.040)	
Average			-0.077			-0.109			-0.032

Notes: The table reports estimates of the Kendall's τ correlation between stock and currency returns in local economies, computed from the non-vine bivariate copula (not including the US stock returns). In addition, it provides the differences between Kendall's τ reported in Table 7 and the one in this table. See also notes in Table 5.

Table 9: Net exports (% of GDP)

Ranking	Economy	Net exports (% of GDP)
1	Norway	12.5
2	Switzerland	9.71
3	Sweden	5.88
4	Chile	5.51
5	Czech Rep.	3.32
6	Korea	3.04
7	Hungary	2.69
8	Indonesia	2.49
9	Euro area	1.99
10	New Zealand	0.77
11	Japan	0.29
12	Brazil	0.25
13	South Africa	-0.53
14	Poland	-1.22
15	Australia	-1.26
16	Mexico	-1.44
17	UK	-2.35
18	Colombia	-3.03
19	Philippines	-3.58
20	India	-3.82
21	Turkey	-4.02

Notes: The table reports the ratio of net exports to GDP, averaged over the period 2003 to 2015 for each economy and ranked in descending order. The data source is World Development Indicators, the World Bank. Taiwan is excluded from the table due to unavailability of the data.

Table 10: Lower tail dependence between stock and currency returns in local economies

	Pre-crisis period			Crisis period			Post-crisis period		
	Vine	Bivariate	Difference	Vine	Bivariate	Difference	Vine	Bivariate	Difference
Australia	0.004 (0.016)	0.097 (0.081)	-0.093	0	0.311 *** (0.066)	-0.311 ***	0	0	
Brazil	0.008 (0.026)	0.024 (0.055)	-0.016	0	0.117 (0.119)	-0.117	0.133 (0.086)	0.251 *** (0.089)	-0.118
Chile	0	0.098 (0.069)	-0.098	0.000 (0.000)	0.057 (0.042)	-0.057	0	0	
Colombia	0.032 (0.046)	0.145 ** (0.072)	-0.113	0.003 (0.009)	0.083 (0.053)	-0.080	0	0	
Czech Rep.	0.059 (0.064)	0.068 (0.073)	-0.008	0	0		0	0	
Euro area	0	0		0	0		0.015 (0.017)	0.007 (0.012)	0.008
Hungary	0.147 * (0.081)	0.187 ** (0.081)	-0.040	0.065 (0.090)	0.097 * (0.054)	-0.033	0.054 (0.062)	0.088 (0.073)	-0.035
India	0.193 ** (0.086)	0.298 *** (0.081)	-0.105	0	0		0	0	
Indonesia	0.259 *** (0.073)	0.316 *** (0.073)	-0.058	0.069 (0.087)	0.149 (0.094)	-0.080	0.145 * (0.075)	0.200 ** (0.083)	-0.055
Japan	0.034 (0.053)	0.089 (0.062)	-0.056	0	0.003 (0.002)	-0.003	0	0	
Korea	0	0.165 ** (0.074)	-0.165 **	0	0		0	0	
Mexico	0.000 (0.000)	0	0.000	0	0.075 (0.074)	-0.075	0.025 (0.049)	0	0.025
New Zealand	0	0		0.007 (0.016)	0.068 (0.043)	-0.061	0	0	
Norway	0	0.000 (0.001)	-0.000	0	0		0	0	
Philippines	0	0.294 *** (0.078)	-0.294 ***	0.150 ** (0.068)	0.215 *** (0.070)	-0.065	0	0	
Poland	0.020 (0.060)	0.117 (0.095)	-0.097	0	0		0	0.012 (0.034)	-0.012
South Africa	0.018 (0.022)	0.057 (0.036)	-0.039	0.157 ** (0.065)	0.212 ** (0.084)	-0.055	0	0	
Sweden	0	0.031 (0.044)	-0.031	0.025 (0.038)	0.148 ** (0.065)	-0.123 *	0	0.022 (0.039)	-0.022
Switzerland	0	0		0	0		0	0	
Taiwan	0	0		0	0		0	0.157 (0.117)	-0.157
Turkey	0.242 *** (0.088)	0.196 * (0.105)	0.046	0	0		0.266 *** (0.055)	0.282 *** (0.073)	-0.016
UK	0	0		0.000 (0.000)	0.096 * (0.055)	-0.096 *	0	0	
Average			-0.069			-0.089			-0.042

Notes: The table reports estimates of the lower tail dependence between stock and currency returns in local economies, computed both from the vine and from the bivariate copula. In addition, it provides their differences. See also notes in Table 5.

Table 11: Upper tail dependence between stock and currency returns in local economies

	Pre-crisis period			Crisis period			Post-crisis period		
	Vine	Bivariate	Difference	Vine	Bivariate	Difference	Vine	Bivariate	Difference
Australia	0	0		0	0.266 ***	-0.266 ***	0.082	0	0.082
					(0.075)		(0.055)		
Brazil	0.008	0.024	-0.016	0	0.117	-0.117	0.308 ***	0.312 ***	-0.004
	(0.026)	(0.055)			(0.119)		(0.079)	(0.082)	
Chile	0	0		0	0.057	-0.057	0	0	
					(0.042)				
Colombia	0	0		0	0		0	0	
Czech Rep.	0.059	0.068	-0.008	0	0		0	0	
	(0.064)	(0.073)							
Euro area	0	0		0	0		0.015	0.007	0.008
							(0.017)	(0.012)	
Hungary	0	0		0.065	0.097 *	-0.033	0	0	
				(0.090)	(0.054)				
India	0	0		0	0		0	0	
Indonesia	0	0.114	-0.114	0.069	0.149	-0.080	0.260 ***	0.255 ***	0.005
		(0.080)		(0.087)	(0.094)		(0.080)	(0.083)	
Japan	0.034	0.089	-0.056	0	0.003	-0.003	0	0	
	(0.053)	(0.062)			(0.002)				
Korea	0	0		0	0		0	0	
Mexico	0	0		0	0.075	-0.075	0.025	0	0.025
					(0.074)		(0.049)		
New Zealand	0	0		0.007	0	0.007	0	0	
				(0.016)					
Norway	0	0		0	0		0.067	0.114 **	-0.046
							(0.060)	(0.057)	
Philippines	0	0		0	0.156 *	-0.156 *	0	0	
					(0.081)				
Poland	0.020	0.098	-0.078	0	0		0	0.218 ***	-0.218 ***
	(0.060)	(0.063)						(0.079)	
South Africa	0.018	0.057	-0.039	0	0.212 **	-0.212 **	0.213 ***	0.278 ***	-0.065
	(0.022)	(0.036)			(0.084)		(0.048)	(0.047)	
Sweden	0	0.031	-0.031	0	0.231 ***	-0.231 ***	0	0.022	-0.022
		(0.044)			(0.069)			(0.039)	
Switzerland	0	0		0	0		0	0	
Taiwan	0	0		0	0		0	0.157	-0.157
								(0.117)	
Turkey	0.242 ***	0.196 *	0.046	0	0		0.266 ***	0.282 ***	-0.016
	(0.088)	(0.105)					(0.055)	(0.073)	
UK	0	0		0	0		0	0	
Average			-0.037			-0.111			-0.037

Notes: The table reports estimates of the upper tail dependence between stock and currency returns in local economies, computed both from the vine and from the bivariate copula. In addition, it provides their differences. See also notes in Table 5.