Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.

Economic Modelling 94 (2021) 401–414

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Financial contagion and contagion channels in the forex market: A new approach via the dynamic mixture copula-extreme value theory

Haiying Wang [a], Ying Yuan [a,*], Yiou Li [b], Xunhong Wang [c]

[a] School of Business Administration, Northeastern University, Shenyang 110169, China
[b] Department of Mathematical Sciences, DePaul University, Chicago, IL 60605, USA
[c] School of Resources and Civil Engineering, Northeastern University, Shenyang 110819, China

ARTICLE INFO

JEL classification:
C32
C51
E42
G15

Keywords:
Financial contagion
Contagion channels
Dynamic mixture copula
Extreme value theory

ABSTRACT

We propose a new approach to the study of financial contagion and contagion channels in the forex market by using a dynamic mixture copula-extreme value theory (DMC-EVT) model. This method allows us to elucidate the complex and dynamic dependence between forex markets. By analyzing 39 currencies that are actively traded on the forex market during the period 2005–2009, our empirical study shows that the DMC-EVT model outperforms the alternative copula models. Furthermore, we confirm the existence of financial contagion in the forex market during the 2007–2009 global financial crisis, and find that wealth constraints are the contagion channel during the crisis. Our results provide important insights on portfolio and risk management.

1. Introduction

The past 30 years have been marked by several financial crises in both developing and developed economies; these include the 1994 Mexican peso collapse, the 1997 Asian financial crisis, and the 2007–2009 global financial crisis (GFC). A typical feature of these crises is that they can spread rapidly from one market to another. This financial feature is generally referred to as 'financial contagion', which is recognized as a threat to economic stability. For instance, the GFC originated in the U.S. subprime mortgage market, spread rapidly across global financial markets on an unprecedented scale, caused worldwide financial disasters, and ultimately resulted in financial system collapse and social unrest (Bekaert et al., 2014). This financial crisis, along with many others, has motivated a large number of financial risk managers, international investors, and scholars to investigate how and why financial contagion occurs, and what actions can be taken to mitigate risk from the crisis source country. Therefore, investigating financial contagion and its mechanism is a core topic in the study of international finance.

Financial contagion appears to prevail in financial markets (e.g., Kokholm, 2016; Alexakis and Pappas, 2018; Apergis et al., 2019; Guidolin et al., 2019; Agosto et al., 2020), and a natural stream of research focuses on the contagion mechanism of financial crises. By understanding the contagion mechanism, investors and risk managers can make appropriate decisions to hedge against market downturns and mitigate risk from the source country. Contagion channels can be roughly divided into two categories: fundamental-induced channels, such as international trade and foreign direct investment (Calvo and Reinhart, 1996); and investor-induced channels (Calvo and Mendoza, 2000). Financial contagion driven by economic fundamentals is called 'shift contagion' (Gravelle et al., 2006), and that induced by investors is called 'pure contagion' (Gómez-Puig and Sosvilla-Rivero, 2016). Wealth constraints and portfolio rebalancing behavior are the commonly recognized channels of investor-induced contagion (e.g., Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Yuan, 2005), and have been extensively studied in the stock market (e.g., Boyer et al., 2006; Petmezas and Santamaria, 2014; Jayech, 2016; Horta et al., 2016). Boyer et al. (2006) conclude that investor-induced contagion in the stock market

* Corresponding author. School of Business Administration, Northeastern University, Zhihui Street, Hunnan district, Shenyang, 110169, China.
E-mail addresses: wanghaiying@stumail.neu.edu.cn (H. Wang), yyuan@mail.neu.edu.cn (Y. Yuan), yli139@depaul.edu (Y. Li), wangxunhong@stumail.neu.edu.cn (X. Wang).

https://doi.org/10.1016/j.econmod.2020.10.002
Received 6 December 2019; Received in revised form 4 October 2020; Accepted 4 October 2020
Available online 13 October 2020
0264-9993/© 2020 Elsevier B.V. All rights reserved.

is caused by wealth constraints across emerging market countries and portfolio rebalancing behavior in developed countries.

Compared with other financial markets, the forex market has several unique and important features that prompt the study of financial contagion in that context. First, unlike other financial markets, the forex market is non-centralized, with no central trading location, and traders can find competing rates from dealers globally. Second, the forex market operates 24 h a day, and tradings occur in a synchronous manner (Celık, 2012). As a result, the transmission mechanism of financial crises in the forex market may differ from that in other financial markets. Third, the forex market has the largest trading volume and liquidity among all financial markets, so it can directly or indirectly influence other financial markets (Wang and Xie, 2016). Lastly, the forex market connects a country's economy and trade with those of other countries. All in all, the forex market affects the balance of international payments and the development of the domestic real economy, and thus it plays a vital role in national security and social stability.

To our knowledge, the literature on financial contagion in the forex market is relatively scarce. Celık (2012), Yang et al. (2016), Kilic (2017) and Cubillos-Rocha et al. (2019) use different approaches to confirm the existence of financial contagion in the forex market. By developing an econometric methodology, Gravelle et al. (2006) find that fundamental-induced contagion in the forex market exists, especially in European countries. Wu et al. (2019) use the Google search volume index as a proxy for investor attention, and show that investors induced the financial contagion in the forex market. However, the authors did not investigate whether the investor-induced contagion was caused by wealth constraints or portfolio rebalancing behavior. This paper aims to fill this gap by proposing a new approach using a dynamic mixture copula-extreme value theory (DMC-EVT) model to systematically study financial contagion and its contagion channels in the forex market.

The literature contains various definitions of financial contagion (see Gravelle et al., 2006; Davidson, 2020), of which the one proposed by Forbes and Rigobon (2002) is the most popular. By their definition, financial contagion is present if a statistically significant increase is observed in cross-market correlation after the occurrence of extreme shocks. Using this definition, many empirical methods have been employed to identify the existence of financial contagion. However, correlation cannot capture the nonlinear dependence that is usually observed between markets. To overcome this, instead of correlation, several recent studies have measured financial contagion based on the dependence between financial markets (e.g., Luo et al., 2015; Zhang and Liu, 2018; Niţoi and Pochea, 2020).

Copula models have been widely used to describe the dependence between financial markets (e.g., Fonseca and Ignatieva, 2019; Fenech and Vosgha, 2019; Ouyang and Zhang, 2020). With a copula model, any multivariate distribution can be estimated by separately estimating the marginal distributions and the copula function. Copula models have also been used to study financial contagion (e.g., Hoesli and Reka, 2015; Jayech, 2016; Zhang and Liu, 2018; Cubillos-Rocha et al., 2019; Niţoi and Pochea, 2020). However, most copula models neglect some aspects of the complex dependence between markets, such as nonlinearity, asymmetry, time-varying patterns, and upper- and lower-tail dependence. For instance, the static mixture copula model (e.g., Horta et al., 2016; Jayech, 2016) describes both upper- and lower-tail dependence and allows them to be asymmetric, but it can't describe the time-varying patterns of the dependence. By adding a dynamic component to the static mixture copula model to construct a dynamic mixture copula (DMC) model, all types of complex dependence mentioned above could be described.

To estimate the marginal distribution, generalized autoregressive conditional heteroscedasticity (GARCH)-type models have commonly been used (Jayech, 2016; Horta et al., 2016; Ji et al., 2018; Fenech and Vosgha, 2019). One drawback of GARCH-type models is that they can't adequately approximate the tail behavior of the marginal distribution, yet the tail behavior is essential in measuring financial contagion. To address this issue, in addition to the GARCH model, the tail of the marginal distribution can be modeled with EVT (Koliai, 2016; Sahamkhadam et al., 2018). In light of this, we construct a DMC-EVT model to describe the joint return distribution of the exchange rate in different forex markets and further estimate the dependence coefficients between those markets. The constructed DMC-EVT model captures the complex tail dependence structure and allows us to precisely measure financial contagion in return.

In this paper, we propose a new approach to investigate the existence of financial contagion and identify its contagion channels in the forex market. The proposed approach consists of three steps. (1) The DMC-EVT model is constructed to estimate the dependence coefficients between forex markets and, based on the dependence coefficients, to determine whether financial contagion exists in the forex market. (2) If financial contagion exists, the econometric methodology proposed by Gravelle et al. (2006) is adopted to identify whether the financial contagion is induced by economic fundamentals or investors. (3) If the financial contagion is investor induced, the DMC-EVT model is applied again to identify whether the financial contagion is a result of wealth constraints or portfolio rebalancing behavior.

We further apply the proposed approach in an empirical study. The data in the study consist of 39 currencies in Europe, North America, Latin America, South America, Asia, Africa, and Oceania. These currencies are actively traded on the forex market and play an important role in international portfolio allocation. Our empirical study shows that the constructed DMC-EVT model outperforms the alternative copula models. Using the proposed approach, we confirm financial contagion from the U.S. to a handful of countries in the forex market. Furthermore, we conclude that the financial contagion in the forex market is induced by investors. Moreover, in Step (3) of the proposed approach, the financial contagion is found to be caused by wealth constraints rather than portfolio rebalancing behavior. These findings can help scholars, international investors, and financial risk managers better understand financial contagion and its mechanism. From a practitioner's perspective, our findings provide important insights and guidance for international investors in the design of corresponding risk-hedging strategies, and for financial risk managers, in the development of effective policies to mitigate risk from the crisis source country.

The paper's contributions are as follows. First, we propose a new three-step approach with a DMC-EVT model to investigate financial contagion and its channels in the forex market. The DMC model can describe the complex dependence between different forex markets, and EVT adequately models the tail behaviors of the marginal distributions. As a result, the constructed DMC-EVT model provides a more precise way to quantitatively measure financial contagion. Our empirical study shows that the DMC-EVT model outperforms other models and facilitates the detection of financial contagion. The contagion channel can then be further identified using Step (2) and (3) of the proposed approach, which therefore yields a reliable analysis of the transmission mechanism of financial crises in the forex market. Notably, the proposed approach is not restricted to studying financial contagion in the forex market, but can also be applied to study financial crises in other markets, such as the COVID-19 crisis in the stock market.

Second, this paper fills the gap in research on the transmission mechanism of financial crises in the forex market, which is of great importance due to the forex market's unique and significant features. Third, using the proposed approach, we empirically investigate financial contagion in the forex market during the 2007–2009 global financial crisis. Our results confirm the existence of financial contagion and identify wealth constraints as the contagion channel. This in-depth examination of the transmission mechanism of financial crises has great practical importance for investors and risk managers seeking to make decisions regarding portfolio selection and financial risk management.

The remainder of the paper is structured as follows. Section 2 describes the data set and summarizes its descriptive statistics. Section 3 introduces the test hypotheses and methodology. Section 4 reports the

Table 1
39 countries and respective forex symbols.

Country	Forex	Country	Forex	Country	Forex	Country	Forex
Panel A: Emerging markets							
Argentina	ARS	China	CNY	Sri Lanka	LKR	Russia	RUB
Brazil	BRL	India	INR	Taiwan, China	TWD	Slovakia	SKK
Chile	CLP	Indonesia	IDR	Thailand	THB	Israel	ILS
Colombia	COP	Malaysia	MYR	Czech Republic	CZK	Morocco	MAD
Mexico	MXN	Pakistan	PKR	Greece	GRD	Turkey	TRY
Peru	PEN	Philippines	PHP	Hungary	HUF		
Panel B: Developed markets							
Australia	AUD	Singapore	SGD	France	FRF	Sweden	SEK
Hong Kong	HKD	South Korea	KRW	Germany	DEM	Switzerland	CHF
Japan	JPY	Belgium	BEF	Italy	ITL	United States	USD
New Zealand	NZD	British	GBP	Spain	ESP	Canada	CAD

empirical results and discusses their practical implications, and Section 5 concludes.

2. Data and its descriptive statistics

In this study, we focus on the financial contagion between the U.S. and international forex markets. We choose daily exchange rates of 39 currencies against the gold ounce[1] in Europe, North America, Latin America, South America, Asia, Africa, and Oceania as our sample (as shown in Table 1). These forex markets include major emerging and developed markets and these 39 currencies are actively traded in global forex markets. Therefore, the sample is considered to be a good representation of the global forex markets.

The daily exchange rates are obtained from the Pacific Exchange Rate Service (http://fx.sauder.ubc.ca/data.html). The sample period begins on January 1, 2005 and ends on December 7, 2009.[2] As suggested by Horta et al. (2016), August 1, 2007, is used to divide the sample into two sub-samples: pre-crisis period data and crisis period data. To avoid spurious dependence between forex markets, any observations where data is missing for at least one market are excluded. The daily log returns of the exchange rates are computed, namely, $r_t = \ln(P_t/P_{t-1})$, where P_t refers to the closing exchange rate of day t. For each forex market, 1183 daily log return observations in the full sample period are obtained, with 610 and 572 observations during the pre-crisis and crisis periods, respectively.

The descriptive statistics of the 39 daily log return series each with 1183 observations are summarized in Table A1 in Appendix A. As shown in Table A1, the sample means are all positive and small, with the smallest one as 0.046% for CLP and the largest one as 0.141% for ITL, and the sample standard deviations are also small ranging from 0.013 to 0.018. Moreover, the distributions of these daily log returns are mostly negatively skewed except COP, MXN, PEN, MYR, and HKD, which are positively skewed. The sample kurtosis is far larger than 3 for all daily log returns, which implies the fat tail of the return distributions. The sample skewness and kurtosis indicate that the probability distributions of all returns are asymmetric and leptokurtic, and the normality assumption seems to be violated. This conjecture is confirmed by the results of Jarque-Bera test. That is, the returns of all considered forex markets exhibit asymmetric phenomena and extreme behavior, and the methods built upon normality assumption are not appropriate to describe the dependence between the sampled forex markets. From the time series analysis perspective, the augmented Dickey–Fuller test shows that the daily returns can be assumed as weakly stationary, and the classical time series models can be applied directly. Based on the Ljung-Box Q (LBQ) test of the returns, some of the daily log returns are serially correlated. Furthermore, the ARCH test suggests that significant heteroscedasticity exists in all series.

3. Methodology

To detect the existence of financial contagion and identify its contagion channels in the forex market, we propose a three-step approach with a DMC-EVT model and formulate the corresponding three hypotheses. To quantitatively measure the financial contagion in a precise way, we construct a DMC-EVT model to describe the complex tail dependence including nonlinearity, asymmetry, and time-varying patterns. Then, in Test 1 (Step (1)), the existence of financial contagion is tested. If the existence of financial contagion is confirmed, in Test 2 (Step (2)), we identify whether financial contagion is induced by investors or economic fundamentals. Finally, in Test 3 (Step (3)), the channel of investor-induced contagion is further distinguished between wealth constraints and portfolio rebalancing behavior.

3.1. Dynamic mixture copula-EVT model

The copula is a function that contains all the information about the dependence between random variables. It allows one to describe any multivariate distribution with its marginal distributions and a copula that describes the dependence structure between the random variables. It is a flexible and effective tool to describe various patterns of dependence structures and has been widely used to measure financial contagion (e.g., Jayech, 2016; Cubillos-Rocha et al., 2019; Fenech and Vosgha, 2019). According to Sklar's (1959) theorem, let Z_1 and Z_2 denote two random variables with bivariate joint distribution function F_{Z_1,Z_2} and two continuous marginal distribution functions F_1 and F_2, then there is a unique copula C: $[0,1]^2 \to [0,1]$ such that

$$F_{Z_1,Z_2}(z_1,z_2) = C(F_1(z_1),F_2(z_2)). \tag{1}$$

One advantage of the copula models is that they can describe the tail dependence, which measures the probability that two variables exhibit extremely small values or extremely large values together. The lower tail dependence coefficient (λ^L) and upper tail dependence coefficient (λ^U) are correspondingly defined as

$$\lambda^L = \lim_{\varepsilon\to 0} P\left[Z_1 < F_1^{-1}(\varepsilon)|Z_2 < F_2^{-1}(\varepsilon)\right] = \lim_{\varepsilon\to 0}\frac{C(\varepsilon,\varepsilon)}{\varepsilon}, \tag{2}$$

$$\lambda^U = \lim_{\varepsilon\to 1} P\left[Z_1 \geq F_1^{-1}(\varepsilon)|Z_2 \geq F_2^{-1}(\varepsilon)\right] = \lim_{\varepsilon\to 1}\frac{1-2\varepsilon+C(\varepsilon,\varepsilon)}{1-\varepsilon}, \tag{3}$$

[1] Various currencies including the U.S. dollar are greatly affected by the GFC and their values are unstable.

[2] As Fitch cut the rating of the long-term Greek debt to BBB$^+$ from A$^-$ on December 8, 2009, bringing the rating of the Greek debt below A$^-$ for the first time in 10 years, December 8, 2009, is considered as the starting date of the sovereign debt crisis. Following Horta et al. (2016), we set December 7, 2009 as the end date for the GFC.

where F_1^{-1} and F_2^{-1} are two marginal quantile functions and $\lambda^L, \lambda^U \in [0,1]$. λ^L being 0 and positive implies independence and dependence of Z_1 and Z_2 in the lower tail, respectively. Larger λ^L suggests stronger dependence. A similar statement holds for the dependence in the upper tail based on the value of λ^U.

3.1.1. Marginal distribution modeling

The GARCH-type models are usually adopted to construct marginal distributions (see Fenech and Vosgha, 2019; Ji et al., 2018). One drawback of the GARCH-type models is that they perform poorly in the tail distribution modeling (Koliai, 2016; Sahamkhadam et al., 2018), while the tail behavior is essential in measuring financial contagion. EVT is a technique that focuses on the tail distribution. It can accurately describe the tail behavior and is usually adopted to depict extreme risk. Therefore, in this work, the GARCH-type models are combined with EVT to construct the marginal distribution.

Suggested by Ji et al. (2018), the AR(1)-GJR(p, q) model with skewed Student-t distribution is adopted to filter autocorrelation and heteroscedasticity. Let r_t and h_t denote the return and conditional variance, respectively. The AR(1)-GJR(p, q) model is expressed as

$$r_t = c_0 + c_1 r_{t-1} + e_t, \tag{4}$$

$$e_t = \sqrt{h_t}\epsilon_t, \tag{5}$$

$$h_t = w + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \gamma_i e_{t-i}^2 I(e_{t-i} < 0), \tag{6}$$

where e_t is the residual, and ε_t is the standardized residual following the skewed Student-t distribution (see Ji et al., 2018 for details).

The peaks over threshold method (Koliai, 2016) of EVT is used for tail distribution modeling. Specifically, the standardized residuals below (above) the predefined threshold value μ_L (μ_U), are fitted by the generalized Pareto distribution. As for the interior part of the marginal distribution, the standardized residuals between μ_L and μ_U are modeled by the empirical distribution function. As a result, the complete marginal distribution constructed by GARCH-EVT model can be written as

$$F(\epsilon) = \begin{cases} \frac{N_{\mu_L}}{N}(1 - \xi_L \frac{\epsilon - \mu_L}{\beta_L})^{-1/\xi_L}, & \epsilon < \mu_L, \\ \widehat{F}(\epsilon), & \mu_L \le \epsilon \le \mu_U, \\ 1 - \frac{N_{\mu_U}}{N}(1 + \xi_U \frac{\epsilon - \mu_U}{\beta_U})^{-1/\xi_U}, & \epsilon > \mu_U, \end{cases} \tag{7}$$

where $N\mu_L$ ($N\mu_U$) is the number of the standardized residuals above (below) the threshold μ_L (μ_U), N is the number of the standardized residuals, ξ_L (ξ_U) is the shape parameter of the lower (upper) tail, β_L (β_U) is the scale parameter of the lower (upper) tail, and $\widehat{F}$ is the empirical distribution function.

3.1.2. Dynamic mixture copulas

In this study, the lower tail dependence and upper tail dependence are the main measurements of financial contagion and contagion channels. Therefore, the copula functions that describe both the upper- and lower-tail dependence are preferred. The Gaussian, Student-t, Clayton, and Gumbel are the commonly used single copulas, and they can capture the overall dependence, symmetrical tail dependence, lower tail dependence, and upper tail dependence, respectively. However, the lower and upper tail dependence often coexist between two financial markets, and asymmetrical behavior is usually observed. To accommodate this, four static mixture copulas, Clayton–Gumbel (CG), Clayton–survival Clayton (CSC), Gumbel–survival Gumbel (GSG), and Symmetric–Joe Clayton (SJC), have been constructed to measure tail dependence (e.g., Jayech, 2016; Wang et al., 2018; Cubillos-Rocha et al., 2019). They can capture both the upper- and lower-tail dependence and allow them to be asymmetric. Liu et al. (2017) and Christensen et al. (2019) show that, compared to single copulas, mixture copulas are more flexible and performed better. However, it is worthwhile to note that the dependence measured by these mixture copulas is assumed to be static, while the real dependence between two financial markets is dynamic and varies with the external market environment (Chiang et al., 2015; Bernardi and Catania, 2018; Dark, 2018; Bu et al., 2019).

Dynamic copula models with different time-varying structures have been developed to describe the dynamic dependence between financial markets (see Manner and Reznikova, 2012 for details). As summarized in Manner and Reznikova (2012), the choice of copulas with different time-varying modeling is a matter of taste and computational capability of the software. As a compromise of estimation precision and computation cost, we use Patton's model (Patton, 2006) as the time-varying modeling for the following reasons: (1) It has been widely used to describe the dynamic dependence in financial markets (e.g., Dias and Embrechts, 2012; Hoesli and Reka, 2015; Luo et al., 2015; Fenech and Vosgha, 2019; Ji et al., 2019; Supper et al., 2020). (2) It is more flexible to fit data compared to dynamic copulas that have some restrictions in the dependence structure. For instance, semiparametric dynamic copula is more suitable for smoothly changing processes (Manner and Reznikova, 2012). (3) It is easy to implement and does not require heavy computation. Then, the Patton's model is added to the previously mentioned four static mixture copulas to construct four dynamic mixture copulas (DMCs), which are dynamic Clayton–Gumbel (DCG), dynamic Clayton–survival Clayton (DCSC), dynamic Gumbel–survival Gumbel (DGSG), and dynamic Symmetric–Joe Clayton (DSJC). The copula function C in Eq. (1) and the corresponding lower and upper tail dependence coefficients regarding the four DMCs are detailed as follows.

(1) The CG copula is expressed as

$$C^{CG}(u,v;k^C,k^G) = \omega C^C(u,v;k^C) + (1-\omega)C^G(u,v;k^G), \tag{8}$$

where ω is the weight parameter with $\omega \in [0,1]$, and C^C and C^G are the Clayton copula and Gumbel copula, respectively.

Adding Patten's model as the dynamic structure, the evolution process of the dependence parameters k^C and k^G in Eq. (8) are defined as

$$k_t^C = \left(w_1 + \beta_1 k_{t-1}^C + \alpha_1 \cdot \frac{1}{10} \sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right)^2, \tag{9}$$

$$k_t^G = 1 + \left(w_2 + \beta_2 k_{t-1}^G + \alpha_2 \cdot \frac{1}{10} \sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right)^2, \tag{10}$$

where $k_t^C \in [0, +\infty)$ and $k_t^G \in [1, +\infty)$. The dependence coefficients of the lower tail and upper tail at time t are correspondingly given by: $\lambda_t^L = \omega \cdot 2^{-1/k_t^C}$, $\lambda_t^U = (1-\omega) \cdot (2 - 2^{1/k_t^G})$.

(2) The CSC copula is expressed as

$$C^{CSC}(u,v;k^C,k^{SC}) = \omega C^C(u,v;k^C) + (1-\omega)C^{SC}(u,v;k^{SC}), \tag{11}$$

where C^C and C^{SC} are the Clayton copula and survival Clayton copula, respectively.

Adding Patten's model as the dynamic structure, the evolution process of the dependence parameters k^C and k^{SC} in Eq. (11) are defined as

$$k_t^C = \left(w_1 + \beta_1 k_{t-1}^C + \alpha_1 \cdot \frac{1}{10} \sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right)^2, \tag{12}$$

$$k_t^{SC} = \left(w_2 + \beta_2 k_{t-1}^{SC} + \alpha_2 \cdot \frac{1}{10} \sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right)^2, \tag{13}$$

where $k_t^C \in [0, +\infty)$ and $k_t^{SC} \in [0, +\infty)$. The dependence coefficients of the lower and upper tails at time t are accordingly given by: $\lambda_t^L =$

$\omega \cdot 2^{-1/k_t^C}$, $\lambda_t^U = (1-\omega)\cdot 2^{-1/k_t^{SC}}$.

(3) The GSG copula is expressed as

$$C^{GSG}(u,v;k^{SG},k^G) = \omega C^{SG}(u,v;k^{SG}) + (1-\omega)C^G(u,v;k^G), \quad (14)$$

where C^{SG} and C^G are the survival Gumbel copula and Gumbel copula, respectively.

Adding Patten's model as the dynamic structure, the evolution process of the dependence parameters k^{SG} and k^G in Eq. (14) are defined as

$$k_t^{SG} = 1 + \left(w_1 + \beta_1 k_{t-1}^{SG} + \alpha_1 \cdot \frac{1}{10}\sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right)^2, \quad (15)$$

$$k_t^{G} = 1 + \left(w_2 + \beta_2 k_{t-1}^{G} + \alpha_2 \cdot \frac{1}{10}\sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right)^2, \quad (16)$$

where $k_t^{SG} \in [1, +\infty)$ and $k_t^G \in [1, +\infty)$. The dependence coefficients of the lower and upper tails at time t are accordingly given by: $\lambda_t^L = \omega \cdot (2 - 2^{1/k_t^{SG}})$, $\lambda_t^U = (1-\omega)\cdot(2-2^{1/k_t^G})$.

(4) The SJC copula is expressed as

$$C^{SJC}(u,v;\lambda^U,\lambda^L) = \omega C^{JC}(u,v;\lambda^U,\lambda^L) + (1-\omega)(C^{JC}(1-u,1-v;\lambda^U,\lambda^L) + u + v - 1), \quad (17)$$

where C^{JC} is the Joe Clayton copula.

Adding Patten's model as the dynamic structure, the dynamic evolution equations of the tail dependence coefficients λ^U and λ^L in Eq. (17) are accordingly specified as

$$\lambda_t^U = \wedge\left(w_1 + \beta_1 \lambda_{t-1}^U + \alpha_1 \cdot \frac{1}{10}\sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right), \quad (18)$$

$$\lambda_t^L = \wedge\left(w_2 + \beta_2 \lambda_{t-1}^L + \alpha_2 \cdot \frac{1}{10}\sum_{i=1}^{10} |u_{t-i} - v_{t-i}| \right), \quad (19)$$

where $\wedge(x) = (1+e^x)^{-1}$.

3.2. The three-step approach: test hypotheses on financial contagion and contagion channels

Test 1 [Step (1)]: The goal of Test 1 is to test the existence of financial contagion between the USD and other forex markets. Compared to the classical correlation, the lower tail dependence coefficient can better account for the danger of extreme shocks (Luo et al., 2015). Thus, we use the mean dependence coefficient of the lower tail calculated with the DMC-EVT model as the measure of financial contagion. If financial contagion exists between two forex markets, the mean dependence coefficient of the lower tail between them should significantly increase in crisis periods compared to tranquil periods. Therefore, the hypotheses to test the existence of financial contagion can be formulated as

$$H_0 : \overline{\lambda}_{cri}^L \le \overline{\lambda}_{p-cri}^L \quad \text{against} \quad H_1 : \overline{\lambda}_{cri}^L > \overline{\lambda}_{p-cri}^L,$$

where $\overline{\lambda}_{cri}^L$ and $\overline{\lambda}_{p-cri}^L$ refer to the mean dependence coefficients of the lower tail between forex markets during the crisis and pre-crisis periods, respectively. The null hypothesis corresponds to no contagion and the alternative hypothesis corresponds to contagion.

According to Choe et al. (2012) and Apergis et al. (2019), the Fisher's z-transformation is used to test the existence of financial contagion. If there is no significant difference between the two dependence coefficients, the z-statistic is approximately normal distribution. That is, under the null hypothesis,

$$z = z_1 - z_2 \sim N\left(0, \frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}\right), \quad (20)$$

where $z_1 = \frac{1}{2}\ln\frac{1+\overline{\lambda}_{cri}^L}{1-\overline{\lambda}_{cri}^L}$, $z_2 = \frac{1}{2}\ln\frac{1+\overline{\lambda}_{p-cri}^L}{1-\overline{\lambda}_{p-cri}^L}$, n_1 and n_2 are the observations of the sample during the pre-crisis and crisis periods, respectively.

Test 2 [Step (2)]: If the financial contagion between the USD and other forex markets is confirmed, the next step is to study the financial contagion channels. The fundamental-induced contagion hypothesis and the investor-induced contagion hypothesis have been widely applied to explain financial contagion under various scenarios (e.g., Caroline and Beatrice, 2001; Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Caramazza et al., 2004; Yuan, 2005). In particular, Gravelle et al. (2006) and Wu et al. (2019) apply these two theories to explain the financial contagion in the forex market. In Test 2, we follow the same theory and assume the financial contagion is either fundamental-based or investor-induced.

According to the econometric methodology proposed by Gravelle et al. (2006), if the impact coefficients of common structure shocks during the crisis period are proportional to those during the tranquil period, the financial contagion is driven by economic fundamentals. Otherwise, the financial contagion is induced by investors. The test statistic θ is constructed as

$$\theta = \max\left\{ \frac{\sigma_{c1}^{cri}\sigma_{c2}^{p-cri}}{\sigma_{c1}^{p-cri}\sigma_{c2}^{cri}}, \frac{\sigma_{c1}^{p-cri}\sigma_{c2}^{cri}}{\sigma_{c1}^{cri}\sigma_{c2}^{p-cri}} \right\}, \quad (21)$$

where σ_{ci}^{p-cri} and σ_{ci}^{cri} are the impact coefficients of common structure shocks for the USD ($i = 1$) and the other forex markets ($i = 2$) during the pre-crisis and crisis periods, respectively (see Appendix B for detailed calculations). Then, the hypotheses distinguishing investor-induced channel and fundamental-induced channel can be formulated as

$$H_0 : \theta = 1 \quad \text{against} \quad H_1 : \theta \ne 1,$$

where the null hypothesis corresponds to investor-induced channel and the alternative hypothesis corresponds to fundamental-induced channel. The statistic θ follows the $\chi^2(1)$ distribution under the null hypothesis H_0.

Test 3 [Step (3)]: If the financial contagion between forex markets is induced by investors, we will further investigate whether the crisis spread through portfolio rebalancing behavior or wealth constraints. As suggested by Kyle and Xiong (2001), Kodres and Pritsker (2002), and Jayech (2016), if the financial contagion is driven by investors' wealth constraints, the dependence in the lower tail should be stronger than that in the upper tail during the financial crisis. Conversely, if the financial contagion is driven by portfolio rebalancing behavior, the lower tail dependence should be weaker than the upper tail dependence. Therefore, the hypotheses to distinguish the channel between portfolio rebalancing behavior and wealth constraints can be formulated as

$$H_0 : \overline{\lambda}_{cri}^L \le \overline{\lambda}_{cri}^U \quad \text{against} \quad H_1 : \overline{\lambda}_{cri}^L > \overline{\lambda}_{cri}^U,$$

where $\overline{\lambda}_{cri}^L$ and $\overline{\lambda}_{cri}^U$ refer to the mean dependence coefficients of the lower and upper tail between forex markets during the crisis period, respectively. The null hypothesis corresponds to portfolio rebalancing behavior and the alternative hypothesis corresponds to wealth constraints. Similarly to Test 1, the hypothesis is tested using the Fisher's z-transformation.

4. Empirical study

4.1. Dynamic mixture copula-EVT model estimation

The AR(1)-GJR(p, q) model is adopted to filter stylized facts such as the fat tail behavior, autocorrelation, and heteroscedasticity. The parameters of AR(1)-GJR(p, q)[3] model are estimated using the maxi-

[3] Due to space limitations, the parameter estimations of the corresponding marginal model are not listed but are available upon request.

mum likelihood estimation (MLE) method, and the values of p and q are selected based on the Akaike information criteria (AIC). Specifically, the AR(1)-GJR(1, 2) model is selected to model the pre-crisis and crisis period returns of SKK and HKD, the AR(1)-GJR(2, 2) model is selected to model the pre-crisis and crisis period returns of HUF, MAD, NZD, SGD, GBP, DEM, ESP, SEK, and USD, the AR(1)-GJR(3, 3) model is selected to model the pre-crisis period return of CHF and crisis period return of BEF, and the AR(1)-GJR(1, 1) model is selected to model the rest of the returns. The LBQ test and ARCH test are performed on the standardized residuals of all returns, and the test results are summarized in Table A2 in Appendix A. As shown in Table A2, the p-values of LBQ and ARCH tests are all larger than 1% for both the pre-crisis and crisis period samples. This suggests that the autocorrelation and heteroscedasticity in the standardized residuals are negligible and the selected models are adequate.

As suggested by Koliai (2016), we use the 10% and 90% percentiles of the standardized residuals as the lower tail threshold (μ_L) and upper tail threshold (μ_U), respectively. Then, the lower and upper tails of the marginal distributions are estimated with the generalized Pareto distribution, and the intermediate part of the marginal distributions are constructed by the empirical distribution function. Since the marginal distributions are required to be uniform(0, 1), the Kolmogorov-Smirnov (K–S) test is conducted for all marginal distributions and the test results are reported in Table A2 in Appendix A. As shown in Table A2, the p-values of all K–S tests are far larger than 1%, from which we can conclude that all marginal distributions are uniform (0, 1) at 1% level. Therefore, the AR-GJR-EVT model can effectively approximate the marginal distributions of the daily log returns and could be used in DMCs to estimate the tail dependence coefficients.

For each pair of forex markets, the four DMCs (DCG, DCSC, DGSG, DSJC) are estimated using the MLE method. According to AIC, the best fitting copula is selected and the tail dependence coefficients between the USD and other forex markets are estimated.[4] The AIC values of the four DMCs for the returns during the pre-crisis and crisis period are listed in Table A3(a) and A4(a) in Appendix A, respectively. In Table A3(a) and A4(a), the underlined number for each pair of forex markets is the smallest AIC, and it corresponds to the best fitting DMC. As shown in Table A3(a), for the pre-crisis period, 1 of 38 pairs of returns is best explained by the DCG, 22 of 38 pairs are best explained by the DGSG, and 15 of 38 pairs are best explained by the DSJC. As shown in Table A4(a), for the crisis period, 1 of 38 pairs is best explained by the DCSC, 36 of 38 pairs are best explained by the DGSG, and 1 of 38 pairs is best explained by the DSJC.

4.2. Copula model comparisons

In this subsection, we compare the performance of the DMC-EVT model with three other types of copula models (static mixture copula-EVT model, dynamic mixture copula model, and static mixture copula model). The static mixture copula-EVT model refers to the static mixture copula model where the marginal distribution is estimated by the AR-GJR-EVT model. The dynamic/static mixture copula model refers to the dynamic/static mixture copula model where the marginal distribution is estimated by AR-GJR model.[5] The AIC values of the four types of copula models are summarized in Table A3 and A4 in Appendix A for data during pre-crisis and crisis periods, respectively. In Table A3 and A4, the boldface number for each pair of forex markets is the smallest AIC value, and it corresponds to the best fitting model. For the data during the pre-crisis period, 18 of 38 pairs are best explained by the DMC-EVT model, 14 of 38 pairs are best explained by the DMC model, 6 of 38 pairs are best explained by the static mixture copula-EVT model, and none of 38 pairs is best explained by the static mixture copula model. Turning to the data during the pre-crisis period, 28 of 38 pairs are best explained by the DMC-EVT model, 3 of 38 pairs are best explained by the DMC model, 7 of 38 pairs are best explained by the static mixture copula-EVT model, and none of 38 pairs is best explained by the static mixture copula model. In general, the constructed DMC-EVT model outperforms the alternative copula models.

4.3. Analysis of financial contagion and contagion channels

4.3.1. Test 1 [Step (1)]: existence of financial contagion

The conclusions of Test 1 are summarized in Table 2. For the pairs of the USD and 13 other forex markets (MXN, INR, CZK, RUB, SKK, MAD, NZD, SGD, KRW, GBP, FRF, ESP, CHF), the mean dependence coefficient of the lower tail during the crisis period is significantly larger than that during the pre-crisis period. Specifically, 10 of the tests are significant at the 1% confidence level, 1 of them is significant at the 5% confidence level, and 2 of them are significant at the 10% confidence level. With this being said, we can conclude that financial contagion exists in these 13 forex markets, while there is not enough evidence to confirm the existence of financial contagion in the other 25 forex markets.

This finding is crucial for investors in the forex market to adjust their risk hedging strategies accordingly. As the existence of the financial contagion could weaken the benefits of portfolio diversification, the risk of portfolios containing foreign exchanges in the U.S. and other contagious countries would increase during the crisis period if the portfolios remain unchanged. Therefore, to reduce the risk of financial loss, the investors, whose portfolios contain foreign exchanges in the U.S. and other contagious countries, may want to change the components or decrease the percentage of the foreign exchanges in the contagious countries during the financial crisis. Alternatively, they can increase the percentage of foreign exchanges that are not affected by the financial crisis.

4.3.2. Test 2 [Step (2)]: investor-induced or fundamental-induced channels

The conclusions of Test 2 discussed in Subsection 3.2 are reported in Table 3. The test statistics θ for all pairs of forex markets are small ranging from 1.002 to 1.283, and they are not significantly different from 1 at the 10% significance level. This implies that the interdependence between the USD and other contagious markets is relatively stable before and during the GFC. Therefore, we can conclude that the reaction of international investors to the shocks during the GFC induced the financial contagion in these forex markets. For instance, when international investors suffer losses from the crisis source country, they may sell assets in other countries possibly due to margin calls, or the investors may rebalance their portfolios toward safe assets such as government bonds. This finding aligns with the conclusion in Wu et al. (2019) which supports that the financial contagion is induced by investors.

The finding that the financial contagion in the forex markets is induced by the investors has important implications for designing effective policies that would prevent or mitigate risk from the crisis source country. As the market fluctuations due to investor-induced contagion last just a few days (Yang et al., 2016), policy-makers should carry out some short-term isolation policies such as capital controls or central bank interventions, to isolate these contagious countries from the crisis source country. Moreover, some short-term stabilizing policies such as tighter monetary policy should be warranted during crisis periods.

[4] Due to space limitations, parameter estimations and tail dependence coefficients of the selected copula are not listed, and they are available upon request.

[5] Indeed, four types of single copula models (the dynamic and static single copula-EVT models, the dynamic and static single copula models) are also compared with the constructed DMC-EVT model, where the four commonly used single copulas (Gaussian, Student-t, Clayton, and Gumbel) are used. The results show that the constructed DMC-EVT model is superior to the four types of single copula models. As space is limited, the AIC values of the single copula models are not listed.

Table 2
Test results for the existence of financial contagion in the forex market.

Forex	$\overline{\lambda}^{L}_{p-cri}$	$\overline{\lambda}^{L}_{cri}$	z	Conclusion	Forex	$\overline{\lambda}^{L}_{p-cri}$	$\overline{\lambda}^{L}_{cri}$	z	Conclusion
ARS	0.751	0.446	−8.464	N	SKK	0.394	0.591	4.502***	C
BRL	0.439	0.466	0.582	N	ILS	0.493	0.531	0.877	N
CLP	0.522	0.377	−3.117	N	MAD	0.162	0.632	9.957***	C
COP	0.573	0.444	−2.993	N	TRY	0.488	0.445	−0.958	N
MXN	0.507	0.622	2.894***	C	AUD	0.627	0.596	−0.856	N
PEN	0.421	0.441	0.423	N	HKD	0.857	0.837	−1.203	N
CNY	0.857	0.839	−1.109	N	JPY	0.451	0.454	0.070	N
INR	0.438	0.546	2.445***	C	NZD	0.319	0.590	5.944***	C
IDR	0.518	0.475	−0.989	N	SGD	0.464	0.529	1.478*	C
MYR	0.851	0.486	−12.506	N	KRW	0.391	0.456	1.372*	C
PKR	0.864	0.445	−14.213	N	BEF	0.673	0.678	0.154	N
PHP	0.615	0.414	−4.740	N	GBP	0.427	0.528	2.252**	C
LKR	0.854	0.394	−14.622	N	FRF	0.423	0.678	6.408***	C
TWD	0.470	0.444	−0.547	N	DEM	0.673	0.677	0.123	N
THB	0.561	0.530	−0.759	N	ITL	0.674	0.678	0.130	N
CZK	0.382	0.644	6.232***	C	ESP	0.420	0.678	6.470***	C
GRD	0.674	0.678	0.130	N	SEK	0.620	0.614	−0.161	N
HUF	0.593	0.539	−1.365	N	CHF	0.477	0.678	5.246***	C
RUB	0.441	0.614	4.147***	C	CAD	0.476	0.486	0.232	N

Notes: ***, **, and * correspondingly denote statistical significance at the 1%, 5%, and 10% levels. “C” means that financial contagion is detected at the 10% level, while “N” indicates that financial contagion is not detected at the 10% level.

Table 3
Results of Test 2 – Investor-induced or fundamental-induced?

Forex	σ^{p-cri}_{c1}	σ^{p-cri}_{c2}	σ^{cri}_{c1}	σ^{cri}_{c2}	θ	Conclusion
MXN	0.011	0.015	0.019	0.024	1.130	Investor-induced
INR	0.011	0.014	0.021	0.023	1.203	Investor-induced
CZK	0.010	0.013	0.021	0.023	1.169	Investor-induced
RUB	0.012	0.014	0.022	0.022	1.102	Investor-induced
SKK	0.012	0.012	0.023	0.023	1.048	Investor-induced
MAD	0.013	0.012	0.021	0.020	1.042	Investor-induced
NZD	0.012	0.010	0.023	0.025	1.283	Investor-induced
SGD	0.014	0.012	0.023	0.021	1.054	Investor-induced
KRW	0.011	0.013	0.021	0.027	1.071	Investor-induced
GBP	0.014	0.011	0.023	0.021	1.202	Investor-induced
FRF	0.013	0.012	0.022	0.020	1.002	Investor-induced
ESP	0.014	0.010	0.023	0.019	1.233	Investor-induced
CHF	0.011	0.012	0.023	0.022	1.143	Investor-induced

Table 4
Results of Test 3 – Wealth constraints or portfolio rebalancing?

Forex	$\overline{\lambda}^{U}_{p-cri}$	$\overline{\lambda}^{L}_{cri}$	z	Conclusion
MXN	0.197	0.622	8.909***	Wealth constraints
INR	0.301	0.546	5.081***	Wealth constraints
CZK	0.428	0.644	5.197***	Wealth constraints
RUB	0.226	0.614	8.199***	Wealth constraints
SKK	0.191	0.591	8.191***	Wealth constraints
MAD	0.203	0.632	9.080***	Wealth constraints
NZD	0.103	0.590	9.678***	Wealth constraints
SGD	0.367	0.529	3.423***	Wealth constraints
KRW	0.353	0.456	2.090**	Wealth constraints
GBP	0.260	0.528	5.427***	Wealth constraints
FRF	0.123	0.678	11.837***	Wealth constraints
ESP	0.123	0.678	11.819***	Wealth constraints
CHF	0.107	0.678	12.096***	Wealth constraints

Note: *** and ** denote statistical significance at the 1% and 5% levels, respectively.

In this situation, the policies aimed at breaking market linkages are unlikely to be successful.

4.3.3. Test 3 [Step (3)]: wealth constraints or portfolio rebalancing

Given that the financial contagion effect of the GFC in these forex markets is induced by investors, we continue to investigate whether the investor-induced contagion is driven by wealth constraints or portfolio rebalancing behavior using Test 3 in Subsection 3.2. The conclusions of Test 3 are listed in Table 4. For each pair of forex markets, the mean dependence coefficient of the lower tail $(\overline{\lambda}^{L}_{cri})$ is greater than that of the upper tail $(\overline{\lambda}^{U}_{p-cri})$ during the crisis period, and all observed z-statistic values are larger than 1.645. As a result, we can conclude that the dependence between these pairs of forex markets in the lower tail is significantly stronger than that in the upper tail. Practically speaking, this indicates that compared to the dependence between the forex markets when the currencies appreciate, the dependence is stronger when the currencies depreciate. In this case, the crisis spreads through wealth constraints instead of rebalancing behavior in the forex market.

To avoid financial contagion associated with wealth constraints, international financial risk managers can provide timely support for struggling financial institutions to reduce investors’ perceived risk. If the crisis spreads to the government deficit level, seeking financial support from international institutions would be a good decision to limit

financial contagion. However, imposing limits on capital movements may not be effective to mitigate the effect of financial contagion, since the crisis doesn't spread through rebalancing behavior.

5. Conclusions

The financial contagion phenomenon recorded in the forex market exhibits serious threats to economic stability. Therefore, investigating financial contagion and its mechanism in the forex market is crucial for policy-makers, financial regulators, and international investors to develop policies and to design strategies accordingly. We propose a novel three-step approach with a DMC-EVT model to detect the existence of financial contagion and to further study the financial contagion channels in the forex market. The constructed DMC-EVT model takes into account the complex dynamics between forex markets such as nonlinearity, asymmetry, time-varying patterns, and tail dependence.

The empirical study shows that the constructed DMC-EVT model outperforms the alternative copula models. That is, the constructed DMC-EVT model measures the financial contagion between forex markets in a more precise way and the proposed approach would lead to a more reliable analysis of financial contagion in the forex market. The analysis results confirm the existence of the financial contagion in the forex market from the U.S. to a handful of countries. This finding provides essential insights for investors to design risk hedging strategies in the forex market. To reduce the risk of financial losses, investors should decrease the percentages of the assets related to the USD and these contagious forex markets, and increase that of the assets in other forex markets which are not affected during the financial crises.

Furthermore, the contagion channels in the forex market are identified. It is found that the financial contagion was caused by wealth constraints during the GFC. To limit the contagion associated with wealth constraints, the international financial risk managers could provide timely support to the struggling financial institutions so as to reduce investors' perceived risk. Also, policy-makers and experts may reevaluate the global financial system regulation and take appropriate reactions to limit the recession. Our findings shed light on the transmission mechanism of the financial crisis in the forex market.

To summarize, the proposed three-step approach provides a reliable tool to analyze the financial contagion in the forex market, and the constructed DMC-EVT model is an efficient statistical model to capture the complex tail dependence such as nonlinearity, asymmetry, and time-varying patterns. The proposed approach with the DMC-EVT model may be applied to other research topics regarding financial contagion and may even have broader applications in the field of financial risk management. For instance, the DMC-EVT model can be used to calculate optimal portfolio weights or to measure the value at risk. As financial crises spread across the entire financial system, the financial contagion may occur in other financial markets such as the sovereign debt market, the credit derivative market, and the energy market. A future research direction could be to investigate the financial contagion phenomenon and contagion mechanism in other financial markets during other financial crises.

Declaration of interest statement

Potential competing interests do not exist in the submission of the enclosed manuscript, and the manuscript is approved by all authors for publication. The work described was original research that has not received prior publication and is not under consideration for publication elsewhere in whole or in part.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are very grateful to the editors and referees for their insightful comments. This work was supported by the National Social Science Foundation of China [grant number 18BJY238].

Appendix A. Additional tables

Table A1
Descriptive statistics of forex market returns.

Forex	Mean(%)	Std	Skewness	Kurtosis	Jarque–Bera	ADF	LBQ	ARCH
ARS	0.083	0.014	−0.256	5.955	443.373***	−34.081***	1.993	97.536***
BRL	0.104	0.015	−0.291	7.871	1185.982***	−35.183***	8.860	133.171***
CLP	0.046	0.018	−0.455	16.931	9606.676***	−38.958***	33.507***	324.839***
COP	0.073	0.015	0.114	8.736	1624.110***	−35.175***	13.969**	219.711***
MXN	0.072	0.016	0.030	7.765	1119.565***	−35.700***	12.235**	215.938***
PEN	0.093	0.016	0.049	12.219	4189.978***	−35.323***	19.679***	357.607***
CNY	0.072	0.015	−0.512	8.519	1553.185***	−34.787***	3.197	122.451***
INR	0.067	0.014	−0.242	5.935	436.256***	−34.624***	2.610	96.623***
IDR	0.089	0.015	−0.195	6.425	585.745***	−35.422***	4.404	136.146***
MYR	0.085	0.015	0.002	7.142	845.499***	−36.492***	11.476**	95.647***
PKR	0.074	0.014	−0.198	6.295	542.752***	−35.409***	5.352	102.093***
PHP	0.113	0.015	−0.034	5.535	316.950***	−34.461***	3.226	106.625***
LKR	0.067	0.015	−0.199	6.189	509.039***	−35.730***	5.785	100.281***
TWD	0.093	0.015	−0.204	5.857	410.516***	−34.212***	2.016	90.718***
THB	0.085	0.014	−0.234	5.944	438.025***	−35.075***	5.897	98.704***
CZK	0.069	0.015	−0.193	5.654	354.496***	−34.563***	3.036	88.375***
GRD	0.060	0.014	−0.546	9.141	1917.823***	−36.923***	8.062	114.812***
HUF	0.074	0.013	−0.366	7.768	1146.839***	−36.765***	9.047	140.073***
RUB	0.082	0.016	−0.325	10.847	3056.234***	−37.464***	13.371**	204.595***
SKK	0.090	0.014	−0.131	6.915	759.015***	−34.873***	3.399	101.849***
ILS	0.053	0.013	−0.405	8.479	1512.087***	−37.123***	11.651**	133.120***
MAD	0.071	0.015	−0.134	6.142	490.132***	−34.801***	3.243	102.727***
TRY	0.104	0.016	−0.196	9.133	1861.762***	−36.979***	17.551***	210.793***
AUD	0.091	0.016	−0.155	8.839	1685.408***	−36.647***	8.474	172.167***
HKD	0.069	0.016	0.073	19.874	14035.836***	−39.308***	65.613***	314.529***
JPY	0.083	0.014	−0.256	5.954	443.055***	−34.138***	1.959	97.393***
NZD	0.071	0.015	−0.360	5.859	428.494***	−34.373***	1.530	129.298***
SGD	0.083	0.015	−0.025	10.547	2807.364***	−36.556***	21.243***	240.715***
KRW	0.069	0.014	−0.300	6.913	772.367***	−35.497***	4.625	119.278***
BEF	0.092	0.017	−0.759	14.713	6875.444***	−34.408***	8.280	139.510***
GBP	0.074	0.013	−0.366	7.766	1146.030***	−36.764***	9.043	140.110***
FRF	0.095	0.014	−0.322	7.965	1235.474***	−35.426***	6.365	133.853***
DEM	0.074	0.013	−0.366	7.767	1146.750***	−36.764***	9.040	140.036***
ITL	0.141	0.018	−0.030	19.790	13895.610***	−33.941***	23.891***	413.061***
ESP	0.074	0.013	−0.366	7.768	1146.898***	−36.765***	9.045	140.069***
SEK	0.074	0.013	−0.366	7.768	1147.000***	−36.765***	9.045	140.055***
CHF	0.086	0.014	−0.061	6.945	767.714***	−36.220***	7.284	139.436***
USD	0.072	0.013	−0.286	6.214	525.201***	−35.989***	5.793	116.010***
CAD	0.071	0.014	−0.299	8.052	1275.576***	−36.685***	9.636*	117.870***

Notes: Std stands for the standard deviation. ADF is the augmented Dickey–Fuller statistic used to test stationarity. LBQ is the Ljung–Box Q statistic used to test autocorrelation at order five. ARCH is used to test heteroscedasticity at order five. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2
Diagnostic test results for standardized residual and K–S test results for marginal distribution.

Forex	Panel A: Pre-crisis period			Panel B: Crisis period		
	LBQ	ARCH	K–S	LBQ	ARCH	K–S
ARS	0.732(0.981)	3.170(0.674)	0.027(0.762)	3.859(0.570)	2.334(0.801)	0.023(0.927)
BRL	0.590(0.988)	1.926(0.859)	0.024(0.851)	7.682(0.175)	2.932(0.710)	0.025(0.853)
CLP	2.612(0.760)	2.775(0.735)	0.030(0.623)	5.699(0.337)	1.918(0.860)	0.025(0.866)
COP	0.316(0.997)	3.100(0.685)	0.025(0.830)	5.245(0.387)	6.757(0.239)	0.025(0.867)
MXN	2.821(0.728)	4.495(0.481)	0.021(0.938)	3.958(0.555)	7.110(0.213)	0.023(0.924)
PEN	0.103(1.000)	1.172(0.948)	0.021(0.949)	5.181(0.394)	6.724(0.242)	0.023(0.927)
CNY	1.404(0.924)	4.735(0.449)	0.022(0.923)	3.135(0.679)	5.099(0.404)	0.024(0.877)
INR	0.674(0.984)	3.866(0.569)	0.022(0.917)	4.026(0.546)	1.752(0.882)	0.025(0.863)
IDR	1.187(0.946)	3.840(0.573)	0.022(0.928)	5.039(0.411)	6.155(0.291)	0.024(0.899)
MYR	1.666(0.893)	1.695(0.890)	0.026(0.790)	3.101(0.684)	4.335(0.502)	0.022(0.947)
PKR	0.606(0.998)	2.738(0.740)	0.023(0.894)	5.928(0.313)	2.207(0.820)	0.024(0.892)
PHP	0.800(0.977)	2.596(0.762)	0.023(0.904)	4.745(0.448)	3.377(0.642)	0.021(0.958)
LKR	0.228(0.999)	6.403(0.269)	0.019(0.978)	6.385(0.271)	1.175(0.947)	0.028(0.752)
TWD	0.497(0.992)	4.590(0.468)	0.023(0.893)	4.586(0.468)	3.121(0.681)	0.025(0.851)
THB	1.205(0.944)	4.879(0.431)	0.020(0.963)	6.602(0.252)	1.691(0.890)	0.021(0.964)
CZK	3.433(0.634)	7.462(0.189)	0.025(0.845)	2.865(0.721)	4.219(0.518)	0.022(0.937)
GRD	1.038(0.959)	11.064(0.050)	0.023(0.904)	6.564(0.255)	3.511(0.622)	0.021(0.966)
HUF	0.922(0.969)	9.211(0.101)	0.025(0.833)	4.906(0.427)	7.070(0.215)	0.030(0.687)
RUB	4.417(0.491)	8.606(0.126)	0.024(0.856)	8.105(0.151)	6.070(0.299)	0.024(0.897)
SKK	1.173(0.947)	10.514(0.062)	0.027(0.740)	4.235(0.516)	4.397(0.494)	0.022(0.945)
ILS	1.430(0.921)	8.978(0.110)	0.022(0.928)	5.001(0.416)	5.405(0.368)	0.023(0.903)
MAD	1.250(0.940)	9.551(0.089)	0.022(0.933)	6.109(0.296)	2.043(0.843)	0.023(0.919)
TRY	3.160(0.675)	5.897(0.316)	0.021(0.941)	3.482(0.626)	0.781(0.978)	0.024(0.887)
AUD	0.634(0.986)	2.104(0.835)	0.023(0.881)	2.997(0.700)	1.909(0.862)	0.022(0.939)
HKD	1.041(0.959)	10.304(0.067)	0.031(0.593)	5.303(0.380)	5.359(0.374)	0.023(0.920)
JPY	0.723(0.982)	3.115(0.682)	0.026(0.804)	3.802(0.578)	2.450(0.784)	0.022(0.944)
NZD	2.152(0.828)	7.678(0.175)	0.024(0.879)	3.782(0.581)	4.223(0.518)	0.022(0.931)
SGD	0.719(0.982)	10.225(0.069)	0.021(0.948)	3.309(0.652)	9.775(0.082)	0.024(0.880)
KRW	0.478(0.993)	5.785(0.328)	0.023(0.891)	4.209(0.520)	3.436(0.633)	0.023(0.912)
BEF	1.012(0.962)	3.101(0.684)	0.023(0.909)	4.383(0.496)	3.961(0.555)	0.022(0.936)
GBP	0.900(0.970)	9.142(0.104)	0.026(0.786)	4.909(0.427)	7.075(0.215)	0.030(0.681)
FRF	3.249(0.662)	8.633(0.125)	0.022(0.930)	6.567(0.255)	5.317(0.378)	0.024(0.890)
DEM	0.911(0.969)	9.181(0.102)	0.025(0.822)	4.912(0.427)	7.067(0.216)	0.030(0.685)
ITL	5.165(0.396)	1.691(0.890)	0.022(0.910)	5.732(0.333)	5.693(0.337)	0.022(0.938)
ESP	0.919(0.969)	9.203(0.101)	0.025(0.830)	4.906(0.427)	7.070(0.215)	0.030(0.686)
SEK	0.917(0.969)	9.208(0.101)	0.025(0.824)	4.909(0.427)	7.066(0.216)	0.030(0.684)
CHF	1.497(0.913)	9.798(0.081)	0.025(0.815)	2.130(0.831)	6.225(0.285)	0.022(0.929)
USD	2.626(0.757)	9.928(0.077)	0.024(0.860)	3.117(0.682)	5.407(0.368)	0.022(0.943)
CAD	1.887(0.865)	10.515(0.062)	0.029(0.662)	4.987(0.417)	3.808(0.577)	0.029(0.719)

Note: The *p*-values for LBQ, ARCH, and K–S tests are listed in the parentheses.

Table A3
AIC values of mixture copula models during the pre-crisis period.

Forex	(a) Dynamic mixture copula-EVT model				(b) Static mixture copula-EVT model			
	DCG	DCSC	DGSG	DSJC	CG	CSC	GSG	DSJC
ARS	−1529.32	−1218.90	**−2022.22**	−1715.99	−1894.21	−1842.88	−1902.47	−1690.81
BRL	−636.61	−595.40	**−650.06**	−629.31	−538.01	−521.84	−551.89	−534.85
CLP	−979.62	−932.75	**−1028.13**	−1003.67	−886.33	−857.67	−903.66	−889.36
COP	−1020.20	−953.48	**−1145.25**	−1062.65	−970.79	−960.63	−982.65	−899.12
MXN	−1130.53	−1052.95	**−1156.56**	−1140.99	−1103.94	−1050.33	−1127.28	−1119.59
PEN	−1365.67	−1219.34	**−2647.41**	−1946.11	−2434.05	−2358.00	−2492.90	−1892.18
CNY	−1453.67	−1115.29	−1701.88	−1834.87	−3231.14	−3100.32	**−3255.42**	−2089.60
INR	−1407.80	−1226.80	−1605.73	−1459.57	−1638.68	−1607.61	**−1641.06**	−1549.38
IDR	−843.85	−824.42	**−885.82**	−846.64	−823.84	−795.63	−824.34	−787.71
MYR	−1478.07	−1117.60	−1650.49	−1694.87	−2360.14	−2281.69	**−2440.27**	−1882.80
PKR	−1446.19	−1284.42	−1552.83	−1675.16	−2250.58	−2215.31	**−2328.02**	−1878.51
PHP	−1241.87	−1226.84	**−1535.42**	−1414.08	−1412.46	−1367.21	−1447.21	−1411.98
LKR	−1439.30	−1277.65	−1690.89	−1904.04	−2337.28	−2245.18	−2379.85	−1905.32
TWD	−1367.53	−1608.57	**−1694.58**	−1417.61	−1555.66	−1513.02	−1586.84	−1498.98
THB	−1205.42	−1030.97	**−1231.36**	−1105.27	−1062.26	−1030.24	−1085.66	−971.02
CZK	−759.71	−697.54	−780.85	−777.69	−649.58	−636.39	−662.43	−675.42
GRD	−874.07	−768.03	−880.37	−900.29	−787.10	−750.66	−813.04	−792.94
HUF	−524.49	−503.73	−540.14	**−565.33**	−478.84	−460.12	−495.76	−513.14
RUB	−1485.10	−1317.85	−1787.59	−1707.51	−1823.52	−1760.14	**−1872.19**	−1716.00
SKK	−674.52	−642.43	−691.64	**−697.43**	−570.63	−553.15	−602.73	−586.64
ILS	−1332.79	−1137.28	**−1338.66**	−1235.99	−1234.76	−1195.13	−1257.87	−1172.53
MAD	−1075.54	−936.64	−1071.07	−1041.45	−986.51	−929.80	−1014.41	−974.61
TRY	−649.10	−644.49	**−671.24**	−636.82	−547.92	−536.12	−565.36	−530.41
AUD	−763.09	−725.74	−777.57	−815.80	−678.61	−650.57	−695.18	−689.59
HKD	−1300.62	−1062.39	−1568.82	−1874.37	−4288.62	−4032.13	**−4401.92**	−2135.44
JPY	−839.93	−829.44	**−913.56**	−878.84	−827.90	−787.45	−847.57	−817.04
NZD	−584.99	−550.91	−605.76	−621.24	−541.60	−522.62	−556.47	−550.81
SGD	−1394.12	−1288.87	**−1684.86**	−1573.61	−1640.42	−1589.27	−1670.78	−1575.64
KRW	−1153.87	−1104.58	**−1268.61**	−1194.26	−1151.40	−1112.93	−1168.42	−1120.71
BEF	−874.76	−764.82	−884.27	−898.03	−787.14	−751.07	−813.00	−792.68
GBP	−806.15	−767.50	−888.67	−874.26	−802.99	−755.77	−825.64	−796.61
FRF	−849.80	−766.98	−899.28	−898.17	−787.00	−751.00	−812.78	−792.68
DEM	−851.71	−765.00	−882.78	−898.06	−786.94	−750.90	−812.72	−792.66
ITL	−874.10	−765.71	−880.34	−900.26	−787.11	−750.69	−813.05	−792.98
ESP	−874.49	−754.79	−899.50	−900.31	−787.20	−751.22	−812.98	−792.85
SEK	−648.89	−614.22	−659.84	**−675.69**	−597.37	−569.25	−610.63	−613.78
CHF	−754.67	−677.11	−775.43	−757.81	−667.79	−644.72	−687.68	−684.72
CAD	−934.04	−853.41	−981.96	−957.31	−896.46	−850.99	−910.05	−916.85

	(c) Dynamic mixture copula-EVT model				(d) Static mixture copula-EVT model			
	DCG	DCSC	DGSG	DSJC	DCG	DCSC	DGSG	DSJC
ARS	−1531.25	−1239.06	−1991.15	−1768.27	−1867.99	−1814.76	−1876.77	−1764.51
BRL	−633.63	−618.59	−649.64	−641.88	−539.74	−527.87	−553.06	−548.07
CLP	−902.80	−861.00	−1014.03	−1008.82	−881.75	−859.31	−899.87	−897.68
COP	−1098.34	−960.66	−1133.35	−1068.95	−967.35	−957.75	−977.69	−916.37
MXN	−1102.55	−1039.74	−1138.39	−1147.71	−1089.15	−1037.30	−1112.63	−1116.95
PEN	−1405.50	−1251.03	−1649.66	−1729.57	−2401.62	−2316.86	−2440.98	−1973.29
CNY	−1490.11	−1111.83	−1700.83	−1900.47	−3129.03	−2999.18	−3145.93	−2207.59
INR	−1420.45	−1300.32	−1604.93	−1593.57	−1601.37	−1582.80	−1631.23	−1563.98
IDR	−858.02	−809.46	−878.07	−858.50	−820.06	−798.84	−820.81	−802.25
MYR	−1490.78	−1219.50	−1710.79	−1935.91	−2332.56	−2221.30	−2366.40	−1939.78
PKR	−1470.82	−1247.73	−1559.03	−1709.44	−2222.73	−2190.07	−2298.68	−1944.61
PHP	−1459.12	−1260.21	−1513.82	−1405.31	−1387.23	−1336.30	−1420.16	−1402.42
LKR	−1464.32	−1302.82	**−2492.55**	−2019.78	−2316.69	−2252.64	−2359.85	−2031.86
TWD	−1367.59	−1429.27	−1609.25	−1539.54	−1521.92	−1482.97	−1557.73	−1507.77
THB	−1017.63	−1091.50	−1205.58	−1106.80	−1038.81	−1014.85	−1072.96	−983.79
CZK	−746.99	−681.30	−769.95	**−794.87**	−650.32	−630.12	−657.08	−677.14
GRD	−883.16	−834.89	−898.37	**−917.86**	−795.39	−760.20	−815.81	−810.51
HUF	−519.58	−501.18	−535.21	−565.21	−473.97	−460.38	−489.26	−512.23
RUB	−1504.68	−1373.41	−1791.82	−1769.81	−1818.25	−1740.27	−1858.17	−1765.64
SKK	−661.01	−635.62	−676.74	−693.59	−571.86	−548.87	−590.55	−585.90
ILS	−1304.68	−1142.22	−1325.54	−1261.49	−1224.62	−1177.26	−1247.08	−1189.55
MAD	−1070.53	−948.99	**−1079.12**	−1064.77	−986.43	−928.21	−1006.66	−997.19
TRY	−635.85	−626.74	−662.34	−647.84	−541.15	−531.55	−555.06	−537.33
AUD	−701.28	−678.86	−772.72	**−822.75**	−679.77	−657.01	−696.73	−701.57

(*continued on next page*)

Table A3 *(continued)*

	(c) Dynamic mixture copula-EVT model				(d) Static mixture copula-EVT model			
	DCG	DCSC	DGSG	DSJC	DCG	DCSC	DGSG	DSJC
HKD	−1297.68	−1070.45	−1557.79	−2032.09	−4251.17	−4124.59	−4358.08	−2295.49
JPY	−884.16	−816.22	−908.50	−893.88	−823.10	−788.68	−843.14	−831.92
NZD	−593.20	−564.12	−608.00	**−627.66**	−544.81	−524.59	−554.23	−559.24
SGD	−1385.83	−1318.94	−1666.97	−1599.27	−1616.44	−1558.29	−1645.61	−1591.13
KRW	−1098.52	−1100.20	−1262.70	−1205.72	−1139.53	−1109.07	−1168.41	−1131.85
BEF	−880.46	−829.96	−895.80	**−915.54**	−793.01	−757.10	−814.30	−808.63
GBP	−860.61	−781.40	−884.48	**−901.20**	−802.69	−761.53	−823.99	−820.11
FRF	−875.62	−831.31	−895.43	**−914.03**	−792.60	−756.71	−814.03	−808.21
DEM	−883.50	−834.79	−898.25	**−917.81**	−795.40	−760.18	−815.82	−810.50
ITL	−883.89	−834.85	−898.69	**−918.04**	−795.53	−760.25	−815.92	−810.72
ESP	−881.46	−830.74	−896.46	**−915.23**	−794.00	−758.16	−815.30	−809.16
SEK	−635.44	−602.97	−647.16	−673.44	−587.16	−561.90	−598.96	−614.49
CHF	−745.62	−683.91	−764.61	**−797.90**	−663.16	−642.06	−680.20	−691.66
CAD	−933.25	−862.74	−985.91	**−1002.52**	−889.37	−855.94	−906.93	−922.97

Note: The underlined number for each pair of forex markets corresponds to the best fitting copula that is selected to estimate the tail dependence, and the boldface number for each pair of forex markets corresponds to the best fitting copula model among the four types of copula models.

Table A4
AIC values of mixture copula models during the crisis period.

Forex	(a) Dynamic mixture copula-EVT model				(b) Static mixture copula-EVT model			
	DCG	DCSC	DGSG	DSJC	CG	CSC	GSG	DSJC
ARS	−1366.00	−1210.95	−1681.10	−1559.19	−1675.74	−1627.11	**−1715.08**	−1568.20
BRL	−488.76	−468.54	**−505.40**	−472.35	−456.68	−439.88	−473.65	−458.17
CLP	−753.21	−737.70	**−800.40**	−754.09	−763.86	−726.70	−779.55	−730.83
COP	−596.06	−585.13	**−621.11**	−589.36	−559.71	−545.72	−570.83	−536.87
MXN	−888.25	−886.13	**−975.51**	−948.87	−869.21	−854.33	−896.09	−836.34
PEN	−1291.20	−1139.82	−1454.45	−1357.62	−1455.86	−1415.92	**−1482.15**	−1352.83
CNY	−1378.52	−1079.12	−1642.39	−1608.24	−3021.95	−2930.09	**−3057.94**	−1877.43
INR	−1088.23	−969.87	**−1139.47**	−1039.49	−1076.26	−1020.16	−1099.04	−1001.66
IDR	−995.44	−919.61	**−1011.61**	−899.53	−979.09	−943.47	−996.96	−934.66
MYR	−1404.37	−1203.56	**−1426.31**	−1365.84	−1386.98	−1317.85	−1406.69	−1363.04
PKR	−1307.28	−1129.96	−1505.76	−1379.14	−1493.19	−1468.67	**−1566.72**	−1376.14
PHP	−1166.73	−1120.19	**−1214.24**	−1169.80	−1180.56	−1129.47	−1195.39	−1165.31
LKR	−1882.83	−1048.52	−2826.89	−1547.36	−2798.94	−2687.65	**−2828.59**	−1797.93
TWD	−1458.07	−1219.11	−1780.67	−1464.92	−1839.36	−1777.84	**−1866.83**	−1629.26
THB	−1333.28	−1237.56	−1759.71	−1445.02	−1545.69	−1486.26	−1586.21	−1420.41
CZK	−497.68	−485.66	**−506.42**	−443.71	−485.07	−473.09	−494.58	−482.35
GRD	−822.46	−798.89	**−842.30**	−813.69	−806.61	−787.05	−827.35	−801.38
HUF	−370.09	−357.11	**−379.78**	−363.08	−345.52	−341.06	−354.96	−342.92
RUB	−996.10	−951.15	**−1162.25**	−1086.10	−1010.37	−983.98	−1005.58	−930.98
SKK	−705.57	−680.80	**−725.93**	−700.44	−696.57	−675.14	−716.00	−693.98
ILS	−850.82	−824.16	**−860.37**	−825.14	−831.48	−806.73	−844.21	−805.56
MAD	−1005.39	−945.55	**−1054.25**	−994.19	−1014.83	−983.33	−1038.34	−991.58
TRY	−528.13	−509.45	**−542.86**	−516.71	−513.90	−497.58	−526.67	−500.71
AUD	−409.91	−400.92	**−418.91**	−402.28	−383.85	−376.12	−396.98	−383.92
HKD	−1247.37	−1041.76	−1452.62	−1615.05	−4110.32	−3890.92	**−4264.17**	−1907.25
JPY	−726.23	−697.69	**−742.10**	−722.78	−719.24	−683.50	−732.87	−700.82
NZD	−358.49	−345.85	−372.42	−364.11	−343.59	−334.78	−355.75	−346.85
SGD	−1274.61	−1490.46	**−1588.15**	−1479.51	−1546.99	−1480.30	−1579.88	−1480.81
KRW	−727.86	−774.73	−774.06	−713.77	−728.12	−713.53	−716.30	−642.20
BEF	−822.43	−798.61	**−842.33**	−821.95	−806.66	−787.09	−827.41	−801.44
GBP	−730.45	−698.03	**−749.56**	−711.85	−705.40	−677.57	−719.92	−680.75
FRF	−822.53	−798.84	**−842.44**	−822.09	−806.69	−787.14	−827.49	−801.58
DEM	−822.61	−775.07	**−842.53**	−822.09	−806.78	−787.22	−827.59	−801.68
ITL	−822.48	−798.60	**−842.31**	−821.85	−806.63	−787.07	−827.37	−801.40
ESP	−822.55	−798.71	**−842.37**	−817.04	−806.68	−787.12	−827.41	−801.43
SEK	−499.63	−488.81	**−518.47**	−458.70	−453.12	−446.68	−463.42	−448.39
CHF	−731.57	−714.16	**−758.79**	−736.03	−713.49	−697.33	−738.70	−719.33
CAD	−601.53	−577.08	**−618.99**	−585.73	−569.45	−547.78	−587.63	−564.11

Forex	(c) Dynamic mixture copula model				(d) Static mixture copula model			
	DCG	DCSC	DGSG	DSJC	DCG	DCSC	DGSG	DSJC
ARS	−1345.36	−1203.99	−1656.73	−1594.47	−1661.03	−1608.20	−1696.40	−1591.68
BRL	−483.98	−463.89	−501.50	−492.89	−455.36	−439.97	−468.94	−462.32
CLP	−757.11	−734.20	−792.53	−759.52	−760.93	−720.84	−771.40	−735.57

(*continued on next page*)

Table A4 *(continued)*

Forex	(c) Dynamic mixture copula model				(d) Static mixture copula model			
	DCG	DCSC	DGSG	DSJC	DCG	DCSC	DGSG	DSJC
COP	−584.86	−573.72	−620.24	−599.00	−557.41	−542.39	−566.24	−546.29
MXN	−900.97	−864.53	−971.62	−948.43	−866.83	−846.70	−886.23	−845.66
PEN	−1283.85	−1174.41	−1438.10	−1404.91	−1437.82	−1392.88	−1431.47	−1368.02
CNY	−1433.55	−1078.15	−1593.68	−1799.51	−2995.61	−2895.34	−3016.05	−2104.38
INR	−1112.25	−978.31	−1134.67	−1060.51	−1079.20	−1029.53	−1096.57	−1017.65
IDR	−993.45	−939.79	−1006.72	−952.50	−976.64	−935.82	−990.22	−949.37
MYR	−1382.27	−1219.50	−1406.63	−1363.33	−1364.46	−1304.41	−1387.95	−1360.67
PKR	−1293.39	−1121.85	−1490.19	−1390.29	−1461.82	−1467.07	−1561.83	−1380.44
PHP	−1186.03	−1095.94	−1205.47	−1181.98	−1167.51	−1124.16	−1186.58	−1169.21
LKR	−1335.44	−1050.87	−1556.61	−1714.49	−2678.36	−2634.77	−2714.80	−1974.86
TWD	−1478.90	−1259.22	−1736.47	−1692.23	−1842.18	−1787.77	−1854.91	−1692.97
THB	−1337.08	−1207.62	**−1769.28**	−1544.64	−1546.47	−1485.97	−1581.00	−1433.74
CZK	−496.00	−487.44	−503.03	−446.51	−484.61	−474.62	−491.71	−487.47
GRD	−800.39	−785.83	−829.78	−818.61	−791.53	−774.15	−816.58	−803.40
HUF	−368.54	−362.76	−378.40	−368.96	−344.21	−339.24	−350.44	−345.62
RUB	−990.34	−947.79	−1146.87	−1096.31	−993.20	−964.84	−1022.12	−949.50
SKK	−696.87	−677.53	−718.20	−706.34	−688.24	−670.86	−708.42	−696.03
ILS	−843.46	−819.02	−860.35	−839.35	−827.45	−803.64	−840.95	−821.93
MAD	−997.48	−947.90	−1047.02	−1013.55	−1005.63	−974.51	−1030.39	−1001.38
TRY	−531.36	−513.75	−538.95	−528.31	−516.06	−500.48	−522.67	−509.79
AUD	−402.40	−382.72	−411.12	−402.82	−376.61	−368.91	−389.32	−383.26
HKD	−1210.17	−1018.86	−1456.72	−1845.90	−4088.38	−3915.88	−4182.28	−2161.82
JPY	−726.23	−700.30	−739.42	−737.40	−719.94	−688.74	−731.76	−724.16
NZD	−358.67	−347.79	−369.01	**−373.61**	−341.74	−334.41	−351.21	−347.17
SGD	−1542.42	−1309.82	−1572.24	−1512.59	−1534.86	−1463.67	−1567.86	−1506.32
KRW	−718.79	−716.76	**−788.58**	−728.43	−717.99	−706.46	−726.27	−663.02
BEF	−806.94	−785.91	−829.92	−818.87	−791.60	−774.21	−816.76	−803.50
GBP	−728.22	−703.18	−748.01	−727.66	−703.24	−678.78	−717.07	−694.13
FRF	−806.72	−785.80	−829.66	−816.86	−791.32	−773.98	−816.41	−803.17
DEM	−806.80	−785.78	−829.79	−814.53	−791.39	−774.09	−816.46	−803.19
ITL	−806.87	−785.84	−829.83	−820.69	−791.53	−774.16	−816.61	−803.42
ESP	−806.71	−785.79	−829.78	−820.67	−791.42	−774.07	−816.57	−803.32
SEK	−493.37	−482.56	−511.83	−504.81	−446.56	−440.85	−457.39	−448.07
CHF	−724.43	−710.31	−750.81	−737.89	−706.93	−694.19	−731.88	−722.96
CAD	−596.41	−572.84	−614.00	−589.41	−563.88	−542.69	−580.43	−568.24

Note: The underlined number for each pair of forex markets corresponds to the best fitting copula that is selected to estimate the tail dependence, and the boldface number for each pair of forex markets corresponds to the best fitting copula model among the four types of copula models.

Appendix B. Calculations of the impact coefficients

Let r_{1t} and r_{2t} denote the forex market returns in the crisis source country and contagious country, respectively. The returns can be decomposed as

$$r_{it} = \mu_i + e_{it}, E(e_{it}) = 0, i = 1, 2, \text{ and } E(e_{1t}, e_{2t}) \neq 0, \tag{22}$$

where μ_i is the expected return of the asset i, and e_{it} is the forecast error. e_{it} can be further decomposed as

$$e_{it} = \sigma_{cit} S_{ct} + \sigma_{it} S_{it}, \quad i = 1, 2, \tag{23}$$

where S_{ct} and S_{it} represent common structure shocks and idiosyncratic structure shocks, respectively, and σ_{cit} and σ_{it} are the impact coefficients of S_{ct} and S_{it}, respectively. The variances of S_{ct} and S_{it} are standardized to unity.

With Eq. (23), there are three moments corresponding to the forecast error variances and covariance, which are expressed as:

$$var(r_1) = \sigma_{c1}^2 + \sigma_1^2, \tag{24}$$

$$var(r_2) = \sigma_{c2}^2 + \sigma_2^2, \tag{25}$$

$$cov(r_1, r_2) = \sigma_{c1}\sigma_{c2}. \tag{26}$$

Furthermore, each type of structural shocks is assumed to switch between low volatility and high volatility regimes. Thus, the impact coefficients of structural shocks in Eq. (23) can be expressed as:

$$\sigma_{cit} = \sigma_{ci}(1 - S_{ct}) + \sigma_{ci}^* S_{ct}, \quad i = 1, 2, \tag{27}$$

$$\sigma_{it} = \sigma_i(1 - S_{it}) + \sigma_i^* S_{it}, \quad i = 1, 2, \tag{28}$$

where the state variables $S_{jt} = \{0,1\}$ with $j = 1,2,c$. The variables with an asterisk correspond to the higher volatility regime (i.e., $|\sigma^*| > |\sigma|$). To allow for sudden jumps in which both common and idiosyncratic structure shocks move between the low volatility and high volatility states, the volatility regimes are assumed to be Markov switching

$$p_r[S_{jt} = 0|S_{jt-1} = 0] = q_j, \tag{29}$$

$$p_r[S_{jt} = 0|S_{jt-1} = 1] = p_j. \tag{30}$$

Based on the high volatility regime for each structural shocks, another five moments are constructed as:

$$var(r_1|S_c = 1) = \sigma_{c1}^{*2} + \sigma_1^2, \tag{31}$$

$$var(r_2|S_c = 1) = \sigma_{c2}^{*2} + \sigma_2^2, \tag{32}$$

$$var(r_1, r_2|S_c = 1) = \sigma_{c1}^{*}\sigma_{c2}^{*}, \tag{33}$$

$$var(r_1|S_1 = 1) = \sigma_{c1}^2 + \sigma_1^{*2}, \tag{34}$$

$$var(r_2|S_2 = 1) = \sigma_{c2}^2 + \sigma_2^{*2}. \tag{35}$$

Combining Eqs. (24)–(26) and Eqs. (31)–(35), one can solve for the eight impact coefficients of structure shocks in Eqs. (27) and (28).

References

Agosto, A., Ahelegbey, D.F., Giudici, P., 2020. Tree networks to assess financial contagion. Econ. Modell. 85, 349–366.

Alexakis, C., Pappas, V., 2018. Sectoral dynamics of financial contagion in Europe–The cases of the recent crises episodes. Econ. Modell. 73, 222–239.

Apergis, N., Christou, C., Kynigakis, I., 2019. Contagion across US and European financial markets: evidence from the CDS markets. J. Int. Money Finance 96, 1–12.

Bekaert, G., Ehrmann, M., Fratzscher, M., Mehl, A., 2014. The global crisis and equity market contagion. J. Finance 69 (6), 2597–2649.

Bernardi, M., Catania, L., 2018. Portfolio optimisation under flexible dynamic dependence modelling. J. Empir. Finance 48, 1–18.

Boyer, B.H., Kumagai, T., Yuan, K., 2006. How do crises spread? Evidence from accessible and inaccessible stock indices. J. Finance 61 (2), 957–1003.

Bu, H., Tang, W., Wu, J., 2019. Time-varying comovement and changes of comovement structure in the Chinese stock market: a causal network method. Econ. Modell. 81 181–104.

Calvo, G.A., Mendoza, E.G., 2000. Rational contagion and the globalization of securities markets. J. Int. Econ. 51 (1), 79–113.

Calvo, S., Reinhart, C., 1996. Capital flows to Latin America: is there evidence of contagion effects? Policy Research Working Paper, pp. 1–33.

Caramazza, F., Ricci, L., Salgado, R., 2004. International financial contagion in currency crises. J. Int. Money Finance 23 (1), 51–70.

Caroline, R.V., Beatrice, W., 2001. Sources of contagion: is it finance or trade? J. Int. Econ. 54 (2), 293–308.

Celık, S., 2012. The more contagion effect on emerging markets: the evidence of DCC-GARCH model. Econ. Modell. 29 (5), 1946–1959.

Chiang, I.E., Hughen, W.K., Sagi, J.S., 2015. Estimating oil risk factors using information from equity and derivatives markets. J. Finance 70 (2), 769–804.

Choe, K., Choi, P., Nam, K., Vahid, F., 2012. Testing financial contagion on heteroskedastic asset returns in time-varying conditional correlation. Pac. Basin Finance J. 20 (2), 271–291.

Christensen, T.S., Pircalabu, A., Høg, E., 2019. A seasonal copula mixture for hedging the clean spark spread with wind power futures. Energy Econ. 78, 64–80.

Cubillos-Rocha, J.S., Gomez-Gonzalez, J.E., Melo-Velandia, L.F., 2019. Detecting exchange rate contagion using copula functions. N. Am. J. Econ. Finance 47, 13–22.

Dark, J., 2018. Multivariate models with long memory dependence in conditional correlation and volatility. J. Empir. Finance 48, 162–180.

Davidson, S.N., 2020. Interdependence or contagion: a model switching approach with a focus on Latin America. Econ. Modell. 85, 166–197.

Dias, A., Embrechts, P., 2012. Modeling exchange rate dependence dynamics at different time horizons. J. Int. Money Finance 29 (8), 1687–1705.

Fenech, J.P., Vosgha, H., 2019. Oil price and gulf corporation council stock indices: new evidence from time-varying copula models. Econ. Modell. 77, 81–91.

Fonseca, J.D., Ignatieva, K., 2019. Jump activity analysis for affine jump-diffusion models: evidence from the commodity market. J. Bank. Finance 99, 45–62.

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

Gómez-Puig, M., Sosvilla-Rivero, S., 2016. Causes and hazards of the euro area sovereign debt crisis: pure and fundamentals-based contagion. Econ. Modell. 56, 133–147.

Gravelle, T., Kichian, M., Morley, J., 2006. Detecting shift-contagion in currency and bond markets. J. Int. Econ. 68 (2), 409–423.

Guidolin, M., Hansen, E., Pedio, M., 2019. Cross-asset contagion in the financial crisis: a Bayesian time-varying parameter approach. J. Financ. Mark. 45, 83–114.

Hoesli, M., Reka, K., 2015. Contagion channels between real estate and financial markets. R. Estate Econ. 43 (1), 101–138.

Horta, P., Lagoa, S., Martins, L., 2016. Unveiling investor-induced channels of financial contagion in the 2008 financial crisis using copulas. Quant. Finance 16 (4), 625–637.

Jayech, S., 2016. The contagion channels of July-August-2011 stock market crash: a DAG-copula based approach. Eur. J. Oper. Res. 249 (2), 631–646.

Ji, Q., Bouri, E., Roubaud, D., Shahzad, S.J.H., 2018. Risk spillover between energy and agricultural commodity markets: a dependence-switching CoVaR-copula model. Energy Econ. 75, 14–27.

Ji, Q., Liu, B.Y., Fan, Y., 2019. Risk dependence of CoVaR and structural change between oil prices and exchange rates: a time-varying copula model. Energy Econ. 77, 80–92.

Kilic, E., 2017. Contagion effects of US Dollar and Chinese Yuan in forward and spot foreign exchange markets. Econ. Modell. 62, 51–67.

Kodres, L.E., Pritsker, M., 2002. A rational expectations model of financial contagion. J. Finance 57 (2), 769–799.

Kokholm, T., 2016. Pricing and hedging of derivatives in contagious markets. J. Bank. Finance 66, 19–34.

Koliai, L., 2016. Extreme risk modeling: an EVT-pair-copulas approach for financial stress tests. J. Bank. Finance 70, 1–22.

Kyle, A.S., Xiong, W., 2001. Contagion as a wealth effect. J. Finance 56 (4), 1401–1440.

Liu, B.Y., Ji, Q., Fan, Y., 2017. Dynamic return-volatility dependence and risk measure of CoVaR in the oil market: a time-varying mixed copula model. Energy Econ. 68, 53–65.

Luo, C., Xie, C., Yu, C., Xu, Y., 2015. Measuring financial market risk contagion using dynamic MRS-Copula models: the case of Chinese and other international stock markets. Econ. Modell. 51, 657–671.

Manner, H., Reznikova, O., 2012. A survey on time-varying copulas specification simulations and application. Econom. Rev. 31 (6), 654–687.

Niţoi, M., Pochea, M.M., 2020. Time-varying dependence in European equity markets: a contagion and investor sentiment driven analysis. Econ. Modell. 86, 133–147.

Ouyang, R., Zhang, X., 2020. Financialization of agricultural commodities: evidence from China. Econ. Modell. 85, 381–389.

Patton, A., 2006. Modeling asymmetric exchange rate dependence. Int. Econ. Rev. 47 (2), 527–556.

Petmezas, D., Santamaria, D., 2014. Investor induced contagion during the banking and European sovereign debt crisis of 2007–2012: wealth effect or portfolio rebalancing? J. Int. Money Finance 49, 401–424.

Sahamkhadam, M., Stephan, A., Östermark, R., 2018. Portfolio optimization based on GARCH-EVT-Copula forecasting models. Int. J. Forecast. 34 (3), 497–506.

Supper, H., Irresberger, F., Weiß, G., 2020. A comparison of tail dependence estimators. Eur. J. Oper. Res. 284 (2), 728–742.

Wang, G.J., Xie, C., 2016. Tail dependence structure of the foreign exchange market: a network view. Expert Syst. Appl. 46, 164–179.

Wang, Y.C., Wu, J.L., Lai, Y.H., 2018. New evidence on asymmetric return-volume dependence and extreme movements. J. Empir. Finance 45, 212–227.

Wu, Y., Han, L., Yin, L., 2019. Our currency, your attention: contagion spillovers of investor attention on currency returns. Econ. Modell. 80, 49–61.

Yang, L., Cai, X.J., Zhang, H., Hamori, S., 2016. Interdependence of foreign exchange markets: a wavelet coherence analysis. Econ. Modell. 55, 6–14.

Yuan, K., 2005. Asymmetric price movements and borrowing constraints: a rational expectations equilibrium model of crises, contagion, and confusion. J. Finance 60 (1), 379–411.

Zhang, G., Liu, W., 2018. Analysis of the international propagation of contagion between oil and stock markets. Energy 165, 469–486.