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The Role of Economic Contagion in the Inward Investment of Emerging Economies: The Dynamic Conditional Copula Approach

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Abstract: Contagion has been one of the most widely studied and challenging problems in recent economic research. This paper aims at capturing the main impact of contagion risk of the U.S. on foreign direct investment inflows in 18 emerging countries. To quantify the degree of contagion, the time-varying tail dependence copula is employed. Then, the Granger causality test and time series regression analysis are used to investigate the temporal and contemporaneous effects of contagion risk on investment inflows, respectively. Overall, the results confirm the time-varying contagion effects of the U.S. economy on 18 emerging economies. The size of contagion effects gradually increases for all countries, except Thailand, the Philippines, Argentina, and Chile. Furthermore, the results of the Granger causality test and regression reveal that temporal and contemporaneous effects of contagion risk on investment inflows exist in 8 out of 18 countries.

Keywords: contagion risk; copula; emerging economies; foreign direct investment; tail dependence; U.S. economy

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1. Introduction

Inward investment can be viewed as a foreign direct investment (*FDI*), which is a vital source of economic growth in many emerging countries [1]. However, there is strong evidence that the economic or financial crisis had a discouraging impact on *FDI* due to the higher macroeconomic uncertainty that resulted from the crisis's contagion [2]. There has been an interest in the economic crises originating in a country and their cross-border transmission, or the contagion effects between one country and another country. There are series of questions that need to be answered to help policymakers in formulating better economic policies. These questions include: How does crisis originating in a country affect other countries? What are the impacts of contagion risks from the economic crisis? We want to note that the contagion effect refers to the extreme correlation coefficients among different economies, and it mainly occurs when the value of correlation coefficients increases during extreme events such as economic crises [3–5].

This paper highlights the impact of one of the more recent economic events, the economic crisis's contagion, on the foreign direct investment (*FDI*) inflows in emerging countries, which are the main trading partners of the U.S. Dornean, Işan, and Oanea [6] revealed that the U.S. economic crisis in 2008 had the most significant impact on *FDI* flows, compared to the past severe crises such as Spain's crisis (1977), Norway's crisis (1987), Finland's crisis (1991), Sweden's crisis (1991), and Japan's crisis (1992). The degree of economic linkages between the U.S. and emerging countries has been proved in many previous works [7–10]. These studies revealed the absence of the contagion effect on emerging countries during the U.S. financial crisis. Although there is a noticeable impact of the U.S. contagion effects on many countries, the impact of this contagion on the *FDI* inflows in emerging economies is limited. The reason is that a contagion effect is an extreme event and rarely occurred in history; thus, the sample size of empirical studies is limited [11]. Moreover, it is not easy to decompose or quantify the actual degree of a contagion effect and its impacts on the *FDI*. In the literature, economists have been interested in the contagion effect since the Mexican devaluation in 1994, which brought capital flows or foreign direct investment (*FDI*) to other Latin American economies, leading to a speculative attack on their currencies [8]. Some works investigated the linkage between contagion and capital flows [6,9,10,12] and revealed a strong linkage. Hernandez, Mellado, and Valdes [12] confirmed that contagion played a significant role in the private capital flows to emerging countries from the 1970s to the 1990s. Dornean, Işan, and Oanea [6] analyzed the effect of the global financial crisis on *FDI* flows into Central and Eastern European (CEE) countries. They found that the contagion occurred during the economic crisis and had a significant contribution to capital flows to the region, but the sign and magnitude of the impact differed notably depending on the specific characteristics of the individual CEE country. However, all of these works used dummy variables to indicate the economic crisis or contagion effect, which may not reflect the actual degree of contagion or economic crisis's impact on capital flows. Specifically, previous studies employed a dummy variable that captures the contagion (economic crisis) and takes the value of 1 for the contagion effect period and 0 otherwise. Although it is difficult to identify the financial crisis period and degree of contagion, the measurement based on tail dependence can solve this problem. Some scholars [4,13–16] suggested that the contagion's degree can be inferred from the extreme co-movement of a pair of random variables as indicated by their lower tail dependence coefficient. In other words, if the lower tail dependence is positive, it signifies the existence of the contagion effect.

This study proposes using the static and dynamic copula models to quantify the degree of the U.S. contagion effect on emerging countries. As the degree of contagion can be reflected by the lower tail dependence, this study presents four tail dependence copulas, namely Student-t, Clayton, rotated Gumbel 180 degrees, and rotated Joe 180 degrees. Specifically, we consider the lower tail dependence between the gross domestic product (GDP) per capita of the U.S. and emerging countries to proxy the degree of contagion effect. In contrast to the related studies [6,9,10,12] that used the dummy variable as the proxy of the contagion effect, our measures mitigate the drawback of using the unreliable indicator and significantly increase the sample size of time span and countries. In particular, the set of emerging countries we consider is selected to detect dissimilarities in contagion effects between the U.S. and emerging countries and within a set of countries belonging to the same geographical area. Thus, our study covers 18 countries in North-South America, Asia, Europe, and Africa from 2005 to 2020.

This research has contributed in three aspects. First is the economic contribution from investigating the U.S. economic contagion effect on the *FDI* inflows in 18 emerging countries in North-South America, Asia, Europe, and Africa using the regression framework. Second, this study also uses the vector autoregressive-based Granger causality test to investigate the causal relationship between the degree of contagion effect and *FDI* inflows in emerging countries. We would like to note that the linear regression and the vector autoregressive-based Granger causality test allow us to reveal, respectively, temporal and contemporaneous effects of contagion risk on *FDI* inflows in emerging economies. The third is the econometric contribution from measuring contagion using both the static and dynamic copulas models as they are the recent powerful tool for estimating the lower tail dependence. Accordingly, this study suggests two conventional tail dependence copulas: Student t-copula (symmetric tail dependence) and Clayton copula (lower tail dependence), and also proposes rotated survival Gumbel (lower tail dependence) and rotated survival Joe (lower tail dependence) copulas to measure the degree of contagion. To the best of our knowledge, this is the first attempt to measure the degree (magnitude) of economic contagion between the U.S. and emerging economies using these four copula functions. In this regard, the tail dependence between *GDP* per capita of the U.S. and that of a particular emerging economy is quantified as the contagion risk. It is also the first study attempting to investigate the impact of the degree of economic contagion on the *FDI* inflows in emerging countries.

The rest of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the econometric methodology. Section 4 defines the variables and provides data descriptions. Section 5 discusses the empirical results, and in Section 6, the conclusion is drawn.

2. Literature Review

2.1. Definition of Economic Contagion

The definition of an economic contagion has been discussed by many in the literature. Dornbusch, Park, and Claessens [17] defined contagion in three perspectives: First, contagion can be defined as the transmission of a shock among economies or markets. Second, contagion is defined as the co-movement of shocks or volatilities among economies or markets. Third, contagion is defined as an increase in the co-movement of volatilities or shocks across economies in a turbulent period. Similarly, Forbes and Rigobon [18] stated that the perceived problem of contagion is only a problem of interdependence, and the economic contagion is represented by a significant increase in cross-country linkages after a shock to one country. Moreover, Bai et al. [19] mentioned that economic contagion is the word used to explain the spreading patterns of economic crisis across countries or regions.

In measuring the economic contagion, Blonigen, Piger, and Sly [20] suggested finding the contemporaneous correlation between countries' macroeconomic variables such as consumption. Kose et al. [21] and Sebestyén and Iloskics [22] suggested analyzing the pairwise correlation between the *GDP* growth among the countries of interest. Thus, in this study, we quantify the economic contagion using the *GDP* growth of the U.S. and emerging economies.

2.2. Econometric Approaches for Measuring the Contagion Risk

Various techniques have been developed to capture and measure contagion between countries, for instance, analysis of the cross-market correlation coefficients [9,23,24], the DCC-GARCH framework [25], and cointegration [26]. The cross-market correlation coefficient is one of the pioneering tools for measuring the contagion effects among markets. It is the most straightforward method that measures the correlation in returns between two markets during a stable period and examines whether there is a significant increase in this correlation coefficient value during the crisis or not. If the correlation coefficient value increases during the crisis, the contagion exists between two markets or countries [23]. Within this context, King and Wadhwani [24] examined the cross-market correlation coefficients among the U.S., U.K., and Japanese stock markets during the U.S. stock market crash in 1987 and found the correlations among these three markets to significantly increase during this period. Likewise, Lee and Kwang [27] employed this approach to detect the contagion effect on 12 major stock markets and confirmed this U.S. stock crisis's contagion effect. Calvo and Reinhart [9] also used this approach to test the contagion effect of the Mexican currency crisis in 1994 on emerging markets. Although the correlation coefficient was successful in detecting the contagion as well as measuring the degree of contagion, Forbes and Rigobon [18] suggested that the test of contagion based on the constant correlation coefficient is misleading and may not correspond to the dynamic and structural change of the economic and financial time series. Moreover, Engle [25] argued that the dynamic correlation is more precise in modeling the time variation of the time series data. Therefore, he introduced the dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model to find the time-varying correlation between markets.

The cross-market correlation framework has been further used to estimate the variance-covariance transmission mechanism across countries. For example, references [7,28,29] applied this method to find evidence of significant contagion across markets after the U.S. stock market crash in 1987 and the Mexican peso crisis in 1994. Chiang, Jeon, and Li [30] confirmed that this model could explain the dynamic correlation of nine Asian stock markets from 1990 to 2003 and showed that the degree of correlation increased significantly during the crisis period.

As the econometric methods improve, many studies gradually recognize the drawbacks of the linear correlation measured by the traditional models. Changqing et al. [3] and Maneejuk, Yamaka, and Sriboonchitta [31] mentioned that most linear correlations measured by those traditional models have a low ability to capture asymmetry and nonlinear dependence. To deal with these problems, Rodriguez [13] suggested measuring the tail dependence between a pair of random variables during the crisis period, and this tail dependence can be quantified by the copulas, which are defined as "functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions" [32]. Compared to the traditional dependency or correlation measurement, copula can characterize a nonlinear, asymmetric dependency, and tail dependence [33]. In addition, the copula model allows us to assess the degree of contagion risk during crisis periods [34]. Thus, this model is an alternative to correlation in the modeling of contagion risks.

However, some scholars [3,4,35–39] argued that the static copula does not consider the structural change in the dependence structure; thus, the dynamic copula model is introduced to find the time-varying tail dependence for full samples to identify the size of "non-crisis" and "crisis" periods through time. Therefore, this paper can quantify the degree of contagion between the U.S. and emerging countries by modeling the dynamic copula model [13]. We would like to note that although the DCC-GARCH can be used to measure the dynamic conditional correlation, this method is bounded by some limitations; particularly, it fails to capture the asymmetric co-movements, tail correlation, and contagion effects that exist in the dynamic behavior among variables [38]. Thus, to overcome this problem, four copulas, namely Student-t, Clayton, rotated survival Gumbel, and rotated survival Joe, are suggested for the dynamic copula models. Note that rotating a copula function allows us to measure the tail with an asymmetric dependence structure.

Our paper is related to the work of [1,12,40,41] in that it investigates the impact of the crisis on the *FDI* inflows in emerging countries. Nevertheless, unlike these previous studies, we replace the dummy variable of crisis with the degree of contagion obtained from the dynamic copula model. Although the dynamic copula model has already been used in many studies to quantify the degree of contagion, previous works focused only on financial markets. Thus, our study is the first attempt ever to measure economic contagion among countries using the dynamic copula model, particularly with the use of rotated survival Gumbel and rotated survival Joe copulas to quantify the time-varying lower tail dependence. To the best of our knowledge, there is no study extending the rotated survival Gumbel and rotated survival Joe copulas for dynamic copula modeling.

2.3. *The Effect of Contagion on Inward Investment*

This study is motivated by the importance of the U.S. crisis's contagion effects on the *FDI* inflows of emerging countries. An increasing number of studies in the literature tried examining the magnitude of economic crises and their contagion effects on *FDI* flows and revealed strong evidence of the considerable economic crisis's contagion influence on *FDI*. Hernandez, Mellado, and Valdes [12] found contagion to play a vital role in determining the level of capital inflow in emerging countries during the 1970s and the 1990s. Hasli, Ibrahim, and Ho[4 0] compared the contagion impact of the U.S. economic crisis with those of the past crises on *FDI* and revealed that the 2008–9 U.S. crisis' contagion was the largest one affecting *FDI* significantly worldwide, particularly that in emerging countries. Likewise, Ucal et al. [1] found the financial crisis to have a negative effect on the *FDI* inflows in 148 emerging countries. Finally, Dornean and Oanea [6] analyzed the impact of the U.S. crisis on *FDI* in Central and Eastern European (CEE) countries and suggested a significant negative impact on CEE *FDI* inflows.

On the other hand, Hasli et al. [41] found that the U.S. financial crisis attracted rather than hindered *FDI* in emerging countries. They explained that although the crisis led to a sell-off of foreign equity holding in the host country, simultaneously, there was an inward flow of *FDI* due to the abolishment of restrictive foreign investment policies to attract new investment. Therefore, multinational enterprises reacted to these attractive and liberalized *FDI* policies by moving their investments into emerging economies during the crises. According to this empirical literature, the studies on the effect of crisis contagion on the *FDI* inflows have illustrated mixed results. Recently, many researchers have questioned how to investigate the impact of the economic contagion on *FDI* since the indicator of economic contagion was generally represented by the dummy variable. Our concern is that the dummy variable might not reflect the actual degree of the contagion of the economic crisis on capital flows. In addition, the contagion might not occur only in the crisis periods.

3. Methodology

This study first uses the dynamic copula models to quantify the tail dependence as a contagion risk for *GDP* growth between the U.S. and each emerging country. Then, the Granger causality test and time series linear regression model are employed to investigate the temporal and contemporaneous effects of contagion risk on *FDI* inflows of emerging countries.

3.1. Bivariate Copula and Tail Dependence

In this study, we use bivariate copula to investigate the economic contagion between the U.S. economy and emerging countries because the model also allows us to measure the degree of contagion through tail dependence. Since Sklar's theorem provided the first definition of a copula, it has two critical implications. First, when the margins are continuous, the copula is unique. Second, it shows that a copula can be constructed from any distribution function with known marginal distributions. Let $H(GDPG^{US}, GDPG^{Dev,i})$ be the joint bivariate distribution function of the standardized gross domestic product (*GDP*) growth of the U.S. and emerging country *i*, respectively. The unique copula function *C* can be presented as

$$H(GDPG^{US}, GDPG^{Dev,i}) = C(F_1(GDPG^{US}), F_2(GDPG^{Dev,i}); \theta), \tag{1}$$

where $F_1(GDPG^{US})$ and $F_2(GDPG^{Dev,i})$ are the empirical cumulative distribution functions of the standardized *GDP* growth of the U.S. and emerging country *i*, respectively, and θ is the copula dependence parameter. Then, we can have a bivariate copula function as

$$C(u^{US}, v^{Dev,i}); \theta) = H(F_1^{-1}(u^{US}), F_2^{-1}(v^{Dev,i})) \tag{2}$$

where $u^{US} = F_1(GDPG^{US})$ and $v^{Dev,i} = F_2(GDPG^{Dev,i})$ are the uniform [0, 1] variables, and F_1^{-1} and F_2^{-1} are the inverse empirical cumulative distribution function. In this study, four copula functions, namely Student-t, Clayton, rotated survival Gumbel, and rotated survival Joe are used to measure the tail dependence.

Tail dependence is the measurement of the dependence between the random variables in the extreme parts of the bivariate distribution [42]. To measure the risk contagion, Chiang et al. [30] suggested capturing the lower tail dependence, which reflects the contagion effect between countries when negative extreme events or crises occur. Therefore, it is reasonable to use the lower tail dependence to measure the economic risk contagion between the U.S. and emerging countries. The lower tail dependence is defined as follows.

$$\tau^L = \lim_{u \to 0} \Pr[F_1(GDPG^{US} < F_1^{-1}(u) | GDPG^{Dev,i} < F_2^{-1}(u)] = \lim_{u \to 0} \frac{C(u, u)}{u}, \tag{3}$$

where $\tau^L \in [0, 1]$, and u is a threshold value. If τ^L is 0, then the U.S. and emerging country *i* have lower tail independence. Note that the higher value of tail dependence indicates the larger size or degree of the contagion risk between the U.S. and emerging country *i*.

As a contagion does not rely on an ad hoc determination of the crisis period, we can use the time-varying copula to measure the contagion size. We focus on time-varying tail dependence by allowing the lower tail parameters to be time-varying according to the ARMA (1,10) process [43,44]. Therefore, we can write the time-varying equations of four copulas models as follows:

The bivariate time-varying tail dependence of Student-t copula is defined as

$$\tau_t^{L(T)} = 2t_{\mathrm{v}+1}\left(-\sqrt{\mathrm{v}+1}\sqrt{\frac{1-\theta_t^{(T)}}{1+\theta_t^{(T)}}}\right), \tag{4}$$

$$\theta_t^{(T)} = \Delta\left(\omega_0^{(T)} + \omega_1^{(T)}\theta_{t-1}^{(T)} + \omega_2^{(T)}\left(\frac{1}{10}\sum_{j=1}^{10} F_1^{-1}(u_{t-j}^{US})F_2^{-1}(v_{t-j}^{Dev})\right)\right), \tag{5}$$

where $t_{\mathrm{v}+1}$ is the standardized Student-t distribution function with $\mathrm{v}+1$ degrees of freedom. $\omega_0^{(T)}$, $\omega_1^{(T)}$, and $\omega_3^{(T)}$ are the estimated parameters. $\theta_t^{(T)}$ is the Student-t copula dependence parameter at time t. Then, we keep the time-varying dependence parameter within the interval $(-1,1)$ by using the transformation function $\Delta(a) = (1-e^{-a})/(1+e^{-a})$. For the degrees of freedom v, the time-varying equation is given by

$$\mathrm{V}_t^{(T)} = \widetilde{\Delta}\left(\gamma_0^{(T)} + \gamma_1^{(T)}\mathrm{v}_{t-1}^{(T)} + \gamma_2^{(T)}\left(\frac{1}{10}\sum_{j=1}^{10} F_1^{-1}(u_{t-j}^{US})F_2^{-1}(v_{t-j}^{Dev})\right)\right), \tag{6}$$

where $\widetilde{\Delta}(a) = 2 + ((e^a/(1+e^{-a})) \times 100)$ is the modified transformation for ensuring $\mathrm{v}_t^{(T)}$ to be within the interval $(-1, \infty)$.

The bivariate time-varying tail dependece of Clayton copula is defined as

$$\tau_t^{L(C)} = 2^{-1/\theta_t^{(C)}}, \tag{7}$$

$$\theta_t^{(C)} = \Delta^C\left(\omega_0^{(C)} + \omega_1^{(C)}\theta_{t-1}^{(C)} + \omega_2^{(C)}\left(\frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j}^{US} - v_{t-j}^{Dev}\right|\right)\right), \tag{8}$$

where $\Delta^C(a) = a^2$ is the modified transformation for ensuring $\theta_t^{(C)}$ to be within the interval $(0, \infty)$.

For the cases of survival Gumbel and survival Joe copulas, their bivariate time-varying tail dependence can be given by

$$\tau_t^{L(S)} = 2 - 2^{1/\theta_t^{(S)}}, \tag{9}$$

$$\theta_t^{(S)} = \Delta^S\left(\omega_0^{(S)} + \omega_1^{(S)}\theta_{t-1}^{(S)} + \omega_2^{(S)}\left(\frac{1}{10}\sum_{j=1}^{10}\left|u_{t-j}^{US} - v_{t-j}^{Dev}\right|\right)\right), \tag{10}$$

where $\Delta^S(a) = 1 + a^2$ is the modified transformation for ensuring $\theta_t^{(S)}$ to be within the interval $(1, \infty)$.

3.2. Copula Functions

- The Student-t Copula

The Student-t copula is an asymmetric dependence model since it has more mass in the tails [15], indicating that it is more likely to produce values far below its mean. The density of the Student-t copula is given by

$$C(u_t^{US}, v_t^{Dev,i}\left|\theta_t^{(T)}, \mathrm{v}_t\right.) = \int_{-\infty}^{t_v^{-1}(u_t^{US})}\int_{-\infty}^{t_v^{-1}(v_t^{Dev,i})} \frac{1}{2\pi\sqrt{1-\theta_t^{(T)}}}\left[1 + \frac{x_t^2 + y_t^2 - 2\theta_t^{(T)}x_t y_t}{\mathrm{v}_t(1-\theta_t^{(T)})^2}\right], \tag{11}$$

where t_v^{-1} is the inverse of the univariate Student-t distribution function with the degrees of freedom v_t; x_t and y_t are the standardized *GDP* growth of the U.S. and emerging country *i*, respectively.

- Clayton Copula

Clayton copula is an implicit copula that exhibits asymmetric dependence for most parameters' values. The lower tail is more dependent than the upper tail, so it may be appropriate for modeling the effect during the crisis [16]. The density of the Clayton copula is

$$C(u_t^{US}, v_t^{Dev,i} \Big| \theta_t^{(C)}) = ((u_t^{US})^{-\theta_t^{(C)}} + (u_t^{Dev,i})^{-\theta_t^{(C)}} - 1)^{1/\theta_t^{(C)}}. \quad (12)$$

This copula has the dependence structure with a range between the independence copula (when $\theta_t^{(C)} = 0$) and as $\theta_t^{(C)} = \infty$ it approaches two-dimensional comonotonicity copula. In other words, it has a lower tail dependence between variables, and it is higher for joint negative events than positive events.

- Rotated copulas

Many copulas cannot display negative tail dependence, for instance, the Gumbel and Joe copulas. Once the bivariate random variable has negative dependence, we can rotate these copulas to capture a negative tail dependence. Cech [15] derived the rotated copula by defining $\overline{u} = 1 - u$ and $\overline{v} = 1 - v$, then the 180° rotated copula is as follows:

$$C^{180^\circ}(u, v) = u + v - 1 + C(1 - u, 1 - v). \quad (13)$$

Thus, we can derive our 180° rotated Gumbel copula $C(u_t^{US}, v_t^{Dev,i} \Big| \theta_t^{(SG)})$ and 180° rotated Joe copula $C(u_t^{US}, v_t^{Dev,i} \Big| \theta_t^{(SJ)})$ as follows:

$$C(u_t^{US}, v_t^{Dev,i} \Big| \theta_t^{(SG)}) = (1 - u_t^{US}) + (1 - u_t^{Dev,i}) - 1 + (\exp(-((1 + \ln u_t^{US})^{\theta_t^{(SG)}} + (1 + \ln u_t^{US})^{\theta_t^{(SG)}}))^{1/\theta_t^{(SG)}}, \quad (14)$$

$$C(u_t^{US}, v_t^{Dev,i} \Big| \theta_t^{(SJ)}) = (1 - u_t^{US}) + (1 - u_t^{Dev,i}) - 1 + (1 - ((-u_t^{US})^{\theta_t^{(SJ)}} + (-u_t^{US})^{\theta_t^{(SJ)}} - (-u_t^{US})^{\theta_t^{(SJ)}} (-u_t^{US})^{\theta_t^{(SJ)}})^{1/\theta_t^{(SJ)}}). \quad (15)$$

3.3. Regression Model

This study investigates the impact of the U.S. contagion risk on the *FDI* inflows in emerging countries using multiple linear regression as predictive analysis. Thus, our empirical model can be written as:

$$\Delta \ln FDI_{i,t} = \beta_{i,0} + \beta_{1,i}\Delta \ln Con_{i,t} + \beta_{2,i}\Delta \ln GDPG_{i,t}^{Dev} + \beta_{3,i}\Delta \ln Open_{i,t} + \beta_{4,i} \ln Exchange_{i,t} + \beta_{5,i}\Delta \ln CPI_{i,t} + \varepsilon_t, \quad (16)$$

where $FDI_{i,t}$ is the ratio of foreign direct investment inflows to *GDP* of country *i* at time *t*. $Con_{i,t}$ is the degree of contagion between the U.S. and emerging country *i* at time *t*. We note that the contagion value is represented by lower tail dependence; thus, $Con_{i,t} = \tau_{i,t}^L$. In addition, we consider additional control variables to avoid the omitted variable problem. We apply the following control variables according to the recommendations of previous literature [41,45–48]. These control variables include real *GDP* per capita of emerging country i,$(GDPG_{i,t}^{Dev})$, trade openness (the ratio of imports + exports to GDP) between the U.S. and emerging country *i* $(Open_{i,t})$, exchange rate U.S. dollar to emerging country's currency *i* $(Exchange_{i,t})$, and consumer price index of emerging country $i(CPI_{i,t})$. $\beta_{0,i}, \beta_{1,i}, \ldots, \beta_{5,i}$ are the estimated coefficients of emerging country's currency *i*. All data are transformed into log differences $\Delta \ln(\cdot)$ to achieve stationary properties.

3.4. Vector Autoregressive-Based Granger Causality Test

In addition to linear regression, the causality relationships are also investigated for *FDI* and contagion risk nexus. Thus, we use the vector autoregressive-based Granger causality test of Rossi [49]. This method is the extension of the traditional Granger causality test of Granger [50]. Rossi [49] mentioned that this method is potentially essential to allow for changes and provides more reliable results in the presence of instabilities than the traditional Granger causality test. In a bivariate framework, the first variable is said to cause the second one in the Granger sense if the forecast for the second variable changes according to the lagged values for the first variable. The specific equation is as follows:

$$\Delta \ln FDI_t = \sum_{p=1}^{P} \alpha_{1p} \Delta \ln Con_{t-p} + \sum_{p=1}^{P} \beta_{1p} \Delta \ln FDI_{t-p} + \varepsilon_{1t}, \quad (17)$$

$$\Delta \ln Con_t = \sum_{1=1}^{P} \alpha_{2p} \Delta \ln Con_{t-p} + \sum_{p=1}^{P} \beta_{2p} \Delta \ln FDI_{t-p} + \varepsilon_{2t}, \quad (18)$$

The null hypothesis of no-Granger causality is given by $H_0 : \alpha_{1p} = 0, H_0 : \beta_{1p} = 0$, and the corresponding alternative hypothesis is $H_0 : \alpha_{1p} \neq 0, H_0 : \beta_{1p} \neq 0$. In other words, the null hypothesis states the non-existence of a causal relationship between the risk contagion and *FDI*. If this null is rejected, there is evidence of Granger causality. To test the above hypothesis, an F-test statistic is used.

4. Definition of Variables and Data Description

4.1. Variables and Data Description

In this paper, we generate tail dependence using the time-varying bivariate copula model for two variables: real *GDP* growth of the U.S. and each emerging country. We also investigate the impact of the contagion risk and other determinants on *FDI* inflows in emerging countries; thus, *GDP* per capita, trade openness, exchange rate, and inflation, and *FDI* inflow data are collected. All the data presented in this study are obtained from www.ceicdata.com (accessed on 1 September 2021) and the World Bank—World Development Indicator. The selected emerging countries include 18 countries, consisting of China, India, Indonesia, Thailand, and the Philippines from the Asian region, Russia, Poland, Hungary, Romania, and Bulgaria from the European region, Brazil, Mexico, Argentina, Chile, and Colombia from the North-South American region, and South Africa, Egypt, and Morocco from the African region, and the U.S. as an origin of the crisis. The paper covers the period of 2005–2020, and the frequency of the data is quarterly, covering 64 observations. We would like to note that although our sample size is small, the results obtained from maximum likelihood estimation (MLE) for our models (bivariate copula, Granger causality, and linear regression) are still valid, as the sample size remains larger than the number of parameter estimates. References [51,52] revealed that MLE for structural equation and regression models are still efficient when the ratio of parameters: sample size is 1:5. In addition, Zhang, Czado, and Min [53] suggested that MLE for the low dimension copula model is still stable and efficient for a small sample size. Table 1 presents the descriptions of all variables considered in this study.

Table 1. Definition of variables.

Variable	Description
Con	Degree of the economic contagion between the U.S. and other emerging countries that is generated by the time-varying tail dependence
GDP^{Dev}	Real *GDP* of the emerging country (USD)
GDP^{US}	Real *GDP* of the U.S. (USD)
Exchange	Growth of real effective exchange rate (local currency/USD) of emerging country
CPI	The consumer price index of emerging country
FDI	Foreign direct investment inflows (million USD)

4.2. Descriptive Statistics

This section presents the descriptive statistics of *GDP* per capita growth of the U.S. and 18 emerging countries in Table 2. We can observe that the mean *GDP* growth is significantly different from zero for all countries. The mean of Chinese *GDP* growth is higher than in other emerging countries. Not surprisingly, China has become the center of the global supply chain network over the past decade. Considering the *GDP* growth in each region, Bulgaria is Europe's largest *GDP* growth country. Argentina and Egypt perform the highest *GDP* growth in North-South American and African regions, respectively.

Table 2. Descriptive statistics for the real *GDP* growth.

	Mean	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**
Argentina	0.0016	0.0174	−0.0240	0.0079	−0.5035	4.4530
Brazil	0.0011	0.0136	−0.0236	0.0053	−1.5417	10.0611
Bulgaria	0.0021	0.0228	−0.0377	0.0174	−0.7522	2.2870
Chili	0.0014	0.0180	−0.0167	0.0070	0.1132	3.3132
China	0.0028	0.0122	−0.0130	0.0075	−1.0107	4.4738
Columbia	0.0013	0.0114	−0.0173	0.0053	−0.9238	4.7650
Egypt	0.0023	0.0252	−0.0406	0.0111	−0.5518	5.5057
Hungary	0.0009	0.0169	−0.0302	0.0118	−0.7903	2.6368
India	0.0017	0.0132	−0.0090	0.0050	0.2774	3.1818
Indonesia	0.0017	0.0132	−0.0090	0.0050	0.2774	3.1818
Mexico	0.0006	0.0083	−0.0205	0.0043	−2.2602	11.6930
Morocco	0.0012	0.0099	−0.0122	0.0035	−0.6776	5.2840
Philippines	0.0024	0.0207	−0.0138	0.0098	−0.0237	5.6870
Poland	0.0012	0.0208	−0.0252	0.0097	−0.4817	3.8526
Romania	0.0016	0.0111	−0.0234	0.0062	−1.4906	6.7158
Russia	0.0015	0.0185	−0.0359	0.0111	−1.5183	5.5273
South Africa	0.0005	0.0148	−0.0212	0.0055	−0.7109	6.1287
Thailand	0.0016	0.0090	−0.0100	0.0034	−0.7348	4.6870
US	0.0026	0.0118	−0.0242	0.0059	−2.0443	9.5837

The minimum, maximum, and standard deviation values indicate that there is a notable time series variation in all variables. For example, Bulgaria shows experiencing the highest and the lowest *GDP* per capita growth of 0.0228 and −0.0377, respectively, among all our sample countries. In addition, compared to other emerging countries, Bulgaria also has the highest standard deviation of *GDP* per capita growth (0.0174), which indicates a high fluctuation of Bulgaria's economy. Conversely, Thailand is the least risky economy since it presents the lowest standard deviation among all our sample countries.

Moreover, most countries (except India, Indonesia, and Chile) show a negative skewness value. This implies that most emerging countries' economic growth has an extended left-tail distribution, while India, Indonesia, Chile have long right-tail distribution. The kurtosis is higher than 3 for all countries, except for Bulgaria and Hungary, and consequently, the distribution of economic growth is leptokurtic.

5. Empirical Results and Discussion

In this section, the unit root test, the dynamic copula, the linear regression, and the VAR models are reported and discussed. The best-fit dynamic copula model is selected using AIC. Finally, the linear regression and the vector autoregressive-based Granger causality test models are then used to investigate the temporal and contemporaneous effects of contagion risk on investment inflows in emerging countries.

5.1. Unit Root Test

Stationarity is the essential requirement for time series analysis. The unit root test is the most effective method for testing the stationarity of a time series. Therefore, we use the augmented Dickey-Fuller (ADF) with intercept and trend test to examine the stationarity.

The null hypothesis is that an observable series is non-stationary (the existence of unit root). According to the ADF test results reported in Table 3, the examined series are stationary for the levels of significance.

Table 3. Unit root test.

Country	Δln*FDI*	Δln*GDPG*	Δln*Open*	Δln*Exchange*	Δln*CPI*
Argentina	−6.1761 ***	−3.4038 **	−4.2294 ***	−4.8897 ***	−5.2225 ***
Brazil	−4.4557 ***	−5.5886 ***	−5.5620 ***	−5.5603 ***	−5.0513 ***
Bulgaria	−3.4568 **	−2.6188 *	−3.0860 **	−5.8374 ***	−3.1764 **
Chili	−2.8136 **	−3.4559 **	−3.7670 ***	−4.9905 ***	−2.5545 *
China	−5.1465 ***	−2.2212 *	−4.1289 ***	−5.5478 ***	−4.4136 ***
Columbia	−4.8532 ***	−5.5249 ***	−4.8687 ***	−5.7841 ***	−1.7821
Egypt	−6.6363 ***	−2.4087 *	−3.0832 **	−4.9364 ***	−5.0002 ***
Hungary	−5.2229 ***	−3.1048 **	−4.8984 ***	−5.9189 ***	−2.6112 *
India	−4.3674 ***	−2.9457 **	−2.8274 **	−4.7345 ***	−2.6418 *
Indonesia	−4.8558 ***	−2.9457 **	−3.6365 ***	−5.2158 ***	−5.8090 ***
Mexico	−6.2830 ***	−5.6129 ***	−3.7025 ***	−5.6368 ***	−2.6060 *
Morocco	−4.2186 ***	−5.2953 ***	−4.5832 ***	−5.7988 ***	−5.7445 ***
Philippines	−4.5965 ***	−5.2953 *	−4.5832 ***	−5.7988 ***	−5.7445 ***
Poland	−5.0173 ***	−3.0119 **	−3.9774 ***	−5.3997 ***	−1.7769 ***
Romania	−3.8397 ***	−5.3349 ***	−4.1205 ***	−5.0965 ***	−2.6095 *
Russia	−3.8870 ***	−2.4474 *	−5.5558 ***	−3.4544 **	−2.4253 *
South Africa	−7.3934 ***	−5.5619 ***	−4.4333 ***	−6.1168 ***	−3.0955 **
Thailand	−5.5904 ***	−4.1589 ***	−4.7394 ***	−3.9255 ***	−7.5076 ***

Note: ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.

Considering the static copulas comparison in Table 4, we can observe that the Student-t copula is selected as the best copula model for virtually all pairs, except for Morocco and South Africa. This indicates that there exists a symmetric tail dependence between the U.S. and emerging countries (except for Morocco and South Africa). For the case of Morocco and South Africa, it is evident that survival Gumbel is the best copula function. The results of the best-fit static copula models are also presented in Table 5. The estimated dependence parameters and their corresponding Kendall's tau, lower and upper tail dependence estimates are provided.

Table 4. Model comparison and tail dependence.

Country	Student-t			Clayton			Survival Gumbel			Survival Joe		
	Upper	Lower	AIC	Upper	Lower	AIC	Upper	Lower	AIC	Upper	Lower	AIC
Argentina	0.29	0.29	**−65.26**	0	0.86	−49.11	0	0.80	−59.19	0	0.86	−47.82
Brazil	0.28	0.28	**−66.95**	0	0.87	−59.32	0	0.80	−65.2	0	0.87	−58.35
Bulgaria	0.32	0.32	**−71.07**	0	0.87	−56.87	0	0.81	−65.87	0	0.87	−55.79
Chile	0.38	0.38	**−84.12**	0	0.88	−66.88	0	0.83	−77.78	0	0.88	−65.91
China	0.38	0.38	**−84.12**	0	0.89	−67.75	0	0.84	−78.45	0	0.89	−67.04
Colombia	0.41	0.41	**−90.21**	0	0.90	−75.85	0	0.85	−85.38	0	0.90	−75.19
Egypt	0.29	0.29	**−64.47**	0	0.86	−50.34	0	0.74	−60.4	0	0.86	−49.36
Hungary	0.41	0.41	**−90.54**	0	0.89	−75.77	0	0.84	−85.14	0	0.90	−75.07
India	0.33	0.33	**−60.25**	0	0.78	−22.43	0	0.72	−30.41	0	0.79	−20.92
Indonesia	0.11	0.11	**−28.78**	0	0.73	−18.57	0	0.67	−24.21	0	0.73	−17.10
Mexico	0.55	0.55	**−129.35**	0	0.93	−114.30	0	0.89	−125.25	0	0.93	−114.05
Morocco	0.19	0.19	−38.53	0	0.82	−40.98	0	0.73	**−42.79**	0	0.82	−41.03
Philippines	0.35	0.35	**−78.09**	0	0.88	−61.61	0	0.82	−72.08	0	0.88	−60.68
Poland	0.36	0.36	**−80.65**	0	0.88	−66.24	0	0.83	−75.78	0	0.89	−65.42
Romania	0.30	0.30	**−66.27**	0	0.86	−52.56	0	0.80	−61.35	0	0.87	−51.41
Russia	0.38	0.38	**−83.32**	0	0.89	−69.24	0	0.83	−78.25	0	0.89	−68.39
South Africa	0.69	0.69	−177.46	0	0.96	−171.42	0	0.93	**−177.73**	0	0.96	−171.39
Thailand	0.35	0.35	**−54.67**	0	0.79	−25.33	0	0.73	-33.03	0	0.80	−23.79

Note: Numbers in the bold present the best static copula.

Table 5. The selected static copula dependence, Kendall's Tau, upper and lower tail dependences between the U.S. and emerging countries.

Country	Selected Copula	Dependence Parameter	Kendall's Tau	Upper Tail	Lower Tail
Argentina	Student-t	0.93	0.76	0.29	0.29
Brazil	Student-t	0.93	0.75	0.28	0.28
Bulgaria	Student-t	0.94	0.77	0.32	0.32
Chile	Student-t	0.95	0.80	0.38	0.38
China	Student-t	0.95	0.80	0.38	0.38
Colombia	Student-t	0.96	0.81	0.41	0.41
Egypt	Student-t	0.93	0.76	0.29	0.29
Hungary	Student-t	0.96	0.81	0.41	0.41
India	Student-t	0.92	0.77	0.33	0.33
Indonesia	Student-t	0.84	0.63	0.11	0.11
Mexico	Student-t	0.98	0.86	0.55	0.55
Morocco	Survival Gumbel	2.90	0.65	0	0.73
Philippines	Student-t	0.94	0.79	0.35	0.35
Poland	Student-t	0.95	0.79	0.36	0.36
Romania	Student-t	0.93	0.76	0.30	0.30
Russia	Student-t	0.95	0.80	0.38	0.38
South Africa	Survival Gumbel	10.74	0.91	0	0.93
Thailand	Student-t	0.91	0.76	0.35	0.35

5.2. Measurement of the Degree of Contagion Effects

This section aims to assess the size of contagion effects between the U.S. and each emerging country by using four copula models to measure the lower tail dependence between them. Specifically, both bivariate static and dynamic copulas are applied to the U.S. and each emerging country's standardized *GDP* growth series. The best-fit static and dynamic copulas are determined by the Akaike information criterion (AIC), with the lowest value of AIC indicating the best copula model. The model comparison results of the static and dynamic copulas are provided in Tables 4 and 6, respectively.

Table 6. Model comparison and average time-varying tail dependence.

Country	Student-t		Clayton		Survival Gumbel		Survival Joe	
	Average Tail	AIC	Average Tail	AIC	Average Tail	AIC	Average Tail	AIC
Argentina	0.28	**−178.98**	0.34	−188.23	0.44	−63.99	0.33	−50.13
Brazil	0.52	−54.87	0.45	**−89.32**	0.29	−73.24	0.78	−61.02
Bulgaria	0.81	**−83.76**	0.78	−65.45	0.77	−70.34	0.87	−62.44
Chile	0.61	**−129.84**	0.62	−121.43	0.43	−100.23	0.45	−70.23
China	0.92	**−102.78**	0.88	−67.75	0.87	−84.54	0.78	−75.52
Colombia	0.81	−121.67	0.85	**−114.98**	0.91	−93.56	0.70	−76.02
Egypt	0.30	**−69.09**	0.45	−63.55	0.40	−65.45	0.43	−62.35
Hungary	0.93	**−100.54**	0.91	−75.77	0.81	−83.26	0.88	−88.24
India	0.53	**−82.53**	0.27	−22.43	0.31	−43.93	0.30	−32.92
Indonesia	0.25	−33.12	0.33	**−36.94**	0.43	−30.11	0.32	−22.23
Mexico	0.83	**−186.09**	0.70	−190.34	0.65	−153.33	0.79	−149.03
Morocco	0.59	−54.87	0.53	−41.04	0.53	**−66.34**	0.49	−41.03
Philippines	0.71	−81.45	0.74	**−102.32**	0.53	−80.32	0.42	−65.94
Poland	0.75	−95.87	0.77	−57.34	0.61	−80.34	0.76	**−104.21**
Romania	0.65	−79.09	0.67	−89.34	0.81	−68.94	0.77	**−93.02**
Russia	0.88	**−98.76**	0.79	−73.23	0.70	−80.23	0.81	−70.35
South Africa	0.83	−178.90	0.82	−171.42	0.82	**−179.73**	0.80	−150.93
Thailand	0.30	**−54.67**	0.25	−25.33	0.20	−39.02	0.23	−51.32

Note: Numbers in the bold present the best dynamic copula result. The average tail is the average tail dependence (reported in Figure 1).

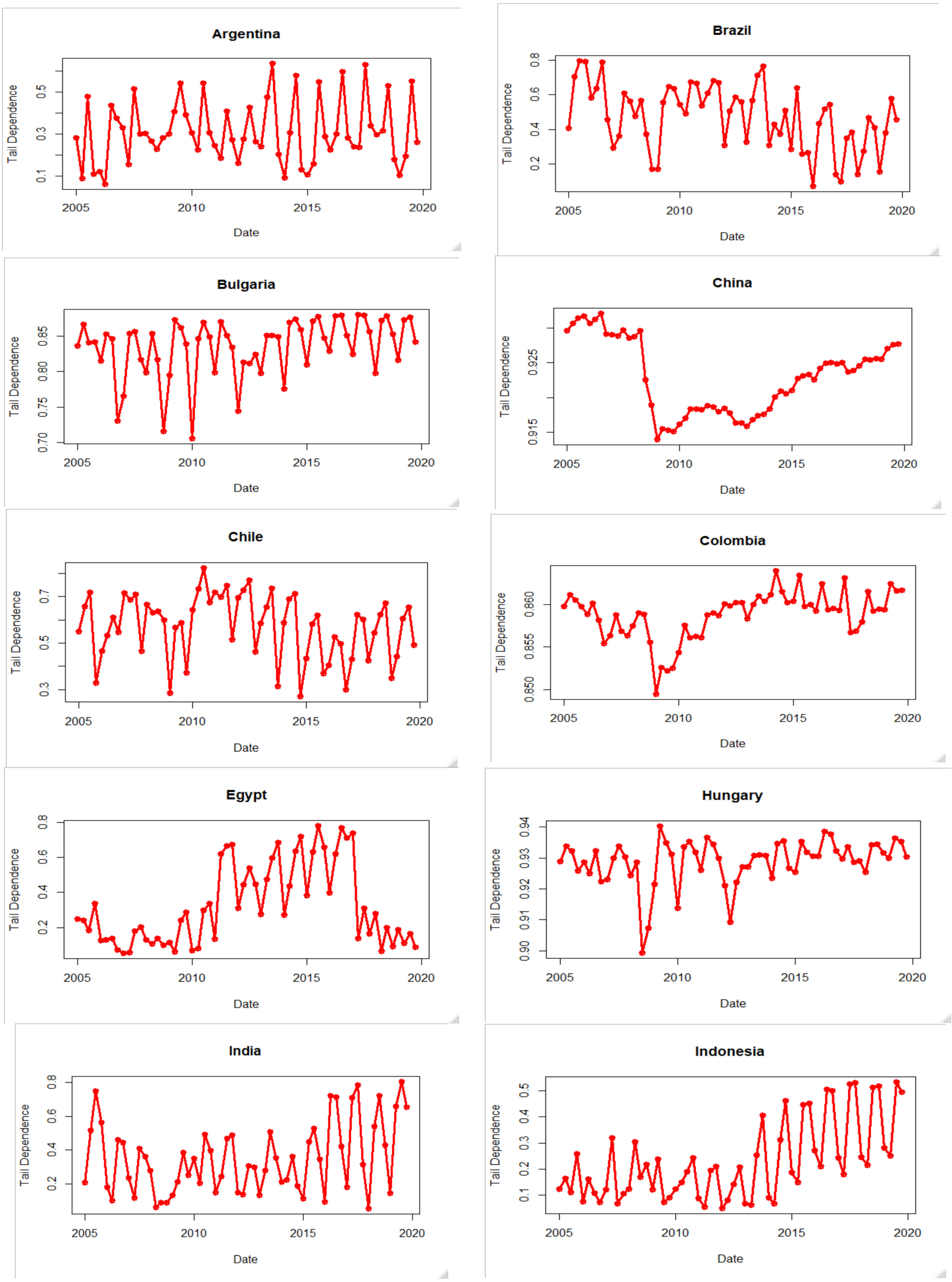

Figure 1. Time-varying tail dependence (contagion risk) between the U.S. economy and emerging countries: Argentina, Brazil, Bulgaria, China, Chile, Colombia, Egypt, Hungary, India, and Indonesia.

The tail dependence results show that the degree of contagion between the U.S. and South Africa is the highest with the value of 0.93, while that in the U.S.-Indonesia pair is the lowest (0.11). This indicates that there is a high impact of the U.S. crisis on South Africa's economic growth. Our result is consistent with the study of [54] that revealed a significant severe impact of the U.S. crisis on South Africa during 2008/09. They also found that South Africa entered the recession in 2008/09 for the first time in 19 years, and the unemployment rate continued to remain high at 25%.

We find that the correlation values are positive in all pairs, ranging from 0.63, the lowest for U.S.-Indonesia, to 0.91, the highest for U.S.-South Africa. Our empirical study is of great interest, given that the results of tail dependence and Kendall's tau are consistent. This indicates that the higher degree of economic integration brings a higher degree of contagion effect. [55] mentioned that the contagion crisis comes from a closer link among the markets, countries, regions, and industries across the world, and this connectivity has become more prominent since the 2008 global financial crisis.

It is of our interest to quantify the degree of contagion over time employing the time-varying copulas. In other words, we consider it is advantageous to allow the time-varying tail dependence copula to interpret the degree of contagion between the U.S. economy and emerging countries throughout the sample period. Again, the four time-varying copulas are also used and compared by the AIC. The comparison results are shown in Table 6. The AIC results suggest that Student-t copula is selected for Argentina, Bulgaria, China, Mexico, Chile, Egypt, Hungary, India, Russia, and Thailand; Clayton is the best choice for Brazil, Colombia, Indonesia, and the Philippines; Survival Joe for Poland and Romania; and survival Gumbel for Morocco and South Africa. This means that the U.S.-emerging economy dependence seems to occur most of the time and during extreme market events. Furthermore, it is evident the presence of asymmetric tail dependence between the economy of the U.S. and the economies of Brazil, Colombia, Indonesia, and the Philippines, Poland and Romania, Morocco, and South Africa. This implies that the economic dependence structure between the U.S. and these countries is not the same in boom and crash.

The estimation results of the best-fit time-varying copulas are reported in Table 7. We note that ω_0 indicates the mean of the dependence, ω_1 indicates autoregressive parameter or degree of persistence, and ω_2 captures the dependence process adjustment [4,39]. We can see that the autoregressive parameter ω_1 in the time-varying copula is significant and less than 0.40, suggesting that there is not a high degree of persistence about the dependence structure between the U.S. and emerging economies. The parameter ω_2 is also strongly significant for all countries except Hungary, indicating substantial variations in the dependence between the U.S. and emerging economies over time. Moreover, this parameter's positive values suggest that the previous information on the growth of the U.S. and emerging countries is useful for investigating the dynamic dependence between them. Nevertheless, it is a fact that the value of the parameter ω_2 is relatively larger compared to the persistence parameter ω_1 for all countries. This means that there is a weak dynamic persistence effect. According to these significant results, we can conclude that the static copula model may not be appropriate to describe the dependence structure between the U.S. and emerging countries' growth.

The average tail dependence or degree of contagion is also reported in Table 7. We can notice that the average tail dependence (column 6) is generally strong (values close to one) in many countries. The highest mean tail dependence, with a value close to 0.94, is obtained for Hungary, followed by China (0.93), Colombia (0.85), Mexico (0.83), South Africa (0.82), Bulgaria (0.81), and Russia (0.78), while the lowest mean tail dependence, with a value close to 0.28, is found in the Indonesia case. This result indicates that the economic growth of Hungary, China, Mexico, Colombia, South Africa, Bulgaria, and Russia is primarily affected by the U.S. contagion risk.

Table 7. The selected dynamic copulas for contagion between the U.S. and emerging countries.

Country	Selected Copula	ω_0	ω_1	ω_2	Average Lower Tail Dependence
Argentina	Student-t	0.124 (0.021) ***	0.364 (0.056) ***	0.635 (0.021) ***	0.33
Brazil	Clayton	0.211(0.101) **	0.320 (0.023) ***	0.679 (0.073) ***	0.45
Bulgaria	Student-t	1.229 (0.631) *	0.132 (0.039) ***	0.282 (0.121) **	0.81
Chile	Student-t	0.321 (0.111) ***	0.321 (0.101) ***	0.678 (0.032) ***	0.61
China	Student-t	1.501 (0.320) ***	0.110 (0.011) ***	0.990 (0.021) ***	0.93
Colombia	Clayton	1.456 (0.522) ***	0.110(0.011) ***	0.990 (0.056) ***	0.85
Egypt	Student-t	0.230 (0.024) ***	0.323 (0.011) ***	0.676 (0.000) ***	0.30
Hungary	Student-t	2.256 (1.428) *	0.056 (0.031) *	0.294 (0.273)	0.94
India	Student-t	1.021 (0.240) ***	0.424 (0.020) ***	0.575 (0.121) ***	0.53
Indonesia	Clayton	0.012 (0.005) **	0.316 (0.037) ***	0.683 (0.069) ***	0.28
Mexico	Student-t	0.515 (0.211) ***	0.315 (0.021) ***	0.684 (0.094) ***	0.83
Morocco	Survival Gumbel	8.693(0.212) ***	0.316 (0.010) ***	0.683 (0.000) ***	0.53
Philippines	Clayton	0.045 (0.010) ***	0.330 (0.021) ***	0.669 (0.091) ***	0.74
Poland	Survival Joe	1.289 (0.244) ***	0.044 (0.041)	0.768 (0.075) ***	0.76
Romania	Survival Joe	1.2445 (0.242) ***	0.154 (0.051) ***	0.443 (0.135) ***	0.77
Russia	Student-t	2.546(1.021) ***	0.210 (0.025) *	0.990 (0.054) ***	0.78
South Africa	Survival Gumbel	3.789 (0.230) ***	0.352 (0.024) ***	0.647 (0.000) ***	0.82
Thailand	Student-t	0.001 (0.000) ***	0.426 (0.022) ***	0.573 (0.043) ***	0.30

Note: ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively. The parentheses () present the standard error.

To better picture the degree of contagion risk over time, we illustrate the time-varying lower tail dependence between the U.S. and various emerging countries generated from the best-fit models presented in Table 7 over the sample period. According to Figures 1 and 2, several observations can be made and summarized as follows: (1) the degree of contagion as reflected by the tail dependence plots for all emerging countries is not stable but varies over time, confirming the appropriateness of the time-varying copulas' implementation rather than the static copulas; (2) after the official ending of the U.S. crisis in 2009, the degree of contagion gradually increased for virtually all countries except Thailand, the Philippines, Argentina, and Chile. This indicates the growing contagion risk of the U.S. in the post-crisis period, which is possibly explained by the growing integration between the U.S. and emerging economies following the implementation of the quantitative easing (QE) policy by the Federal Reserve (Fed) [56]. In 2008, the Fed announced the first QE to escape from the severe crisis. This policy was employed during 2008–2014, and it has led the Fed's balance sheet to increase from less than USD $1 trillion in 2008 to USD $4.4 trillion in 2014. Çepni et al. [57] mentioned that a large surge in capital flows to emerging countries has occurred after the global financial crisis in 2008 due to the low savings rate in the U.S.

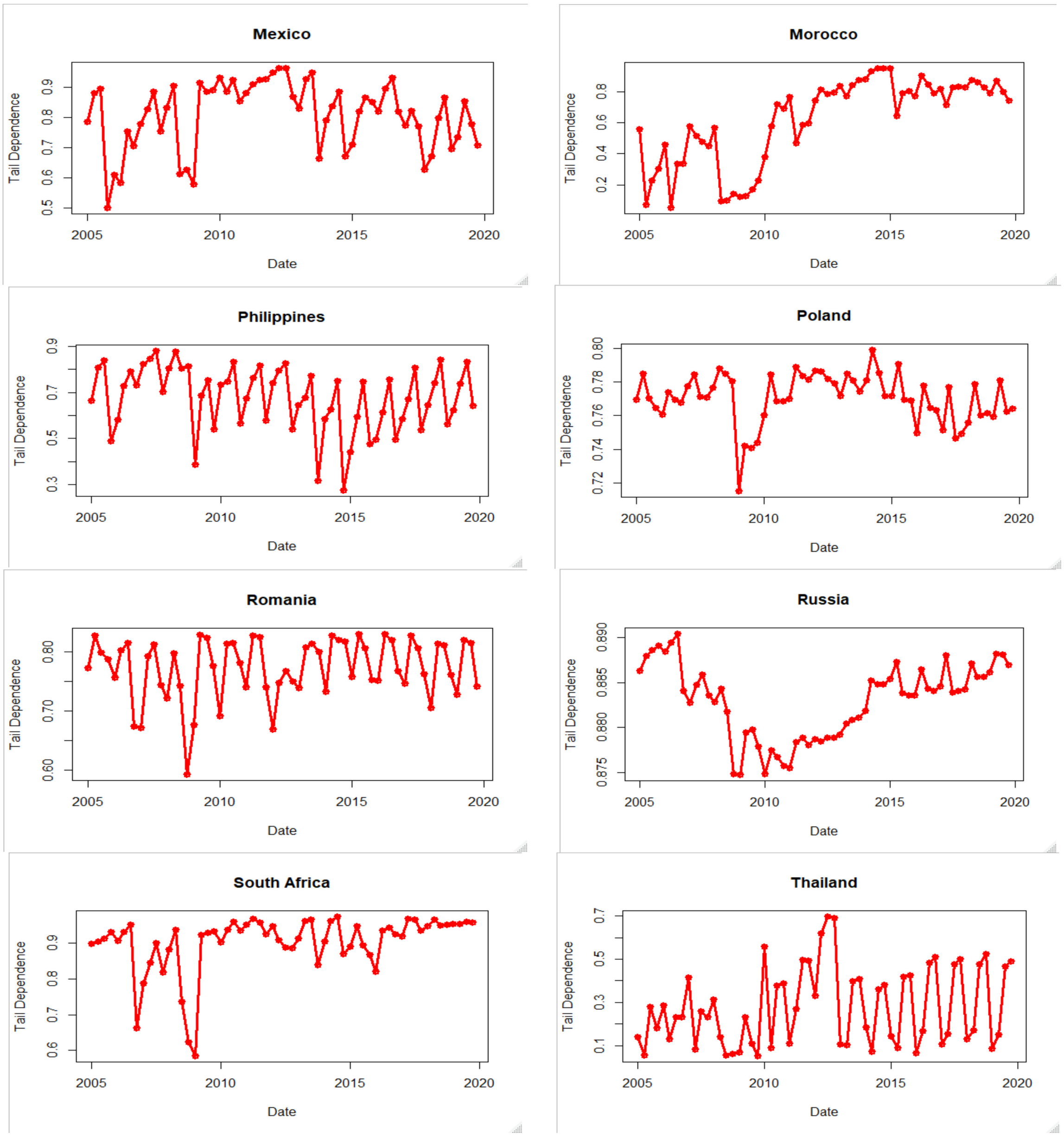

Figure 2. Time-varying tail dependence (contagion risk) between the U.S. economy and emerging countries: Mexico, Morocco, the Philippines, Poland, Romania, Russia, South Africa, and Thailand.

Thus, these large capital inflows resulted in the high national debt in emerging countries and led to significant instability in their financial markets and economies. (3) Among the emerging countries, the degree of contagion between the U.S. and Hungary exhibits the highest values, with the time-varying dependence reaching a low of 0.90 and a high of 0.94. In contrast, the U.S.-Indonesia contagion exhibits the lowest values with the time-varying dependence ranging from 0.06 to 0.52. This result reveals that the Hungarian economy has been substantially affected by the external contagion risk from the U.S. economy for most of the time from 2005 to 2019. Our finding is consistent with the study results of Egedy [58] on the influence of the global financial crisis on Europe, which indicates that Hungary is one of the biggest losers of the crisis in Europe as it is a small country with an open economy and has a weak fiscal policy stance. Since 2009, the Hungarian currency has been depreciated by 17 percent compared to the EUR; thus, it has ruined its export sector and many industries. [59] pointed out that Hungary has shown such vulnerability to global developments and has been forced to obtain external support from the IMF. At the end of 2009, the number of housing loans in Hungary was 3920 billion HUF (i.e., 15 percent of the GDP), of which 63 percent was the ratio of foreign currency-based housing loans. (4) Interestingly, the tail dependence correlation is relatively high in European countries (the average tail dependence above 0.77 for all European countries), indicating that the crisis affected the European region more than other regions.

5.3. Vector Autoregressive-Based Granger Causality Test Results

The contagion effect between the U.S. and various emerging countries is captured from the time-varying tail dependence copulas and is presented in the previous section. We then examine causality between the U.S. contagion effect and *FDI* flows to emerging countries. Granger causality tests are applied based on the VAR model presented in Section 3.4. Table 8 reports the F-test for Granger causality between the tail dependence as a contagion effect and *FDI* inflows at various lags in the 18 countries.

Table 8. Granger causality test for lags 1–3 (F-statistic test).

Country	*FDI* → Contagion			Contagion → *FDI*		
	$p = 1$	$p = 2$	$p = 3$	$p = 1$	$p = 2$	$p = 3$
Argentina	0.3107	0.2699	1.4719	0.1606	0.1439	0.9681
Brazil	1.3769	0.9123	0.49830	0.3508	0.8135	0.5025
Bulgaria	1.1139	4.6332 **	3.2283 **	0.1977	1.4251	1.0065
Chile	1.7411	6.9746 ***	5.2557 ***	3.9477 *	0.19930	0.4257
China	0.6281	2.8796	0.6449	5.3808 **	3.9931 **	3.752 **
Colombia	1.4796	3.9657 **	2.4044 *	0.55380	0.3769	0.4483
Egypt	1.6925	2.9058 *	2.344 *	3.4067 *	0.6571	2.2800 *
Hungary	1.4604	0.8182	0.4474	4.3403 **	1.1707	1.2185
India	0.1641	0.6084	0.4270	1.2172	0.2632	0.4151
Indonesia	1.1480	0.8111	0.5182	0.3891	0.4861	0.4943
Mexico	0.2916	0.8634	0.6253	0.8557	0.4133	0.3532
Morocco	1.2401	0.0531	0.0564	0.7824	1.0372	0.8307
Philippines	3.0568	2.3505	1.7870	0.0474	1.2331	0.8382
Poland	0.5130	0.1509	0.1144	1.7416	1.1332	0.8912
Romania	1.3345	4.531 **	2.1743	6.3311 **	1.4152	1.2072
Russia	1.1171	2.2771	2.9827 **	0.6898	0.2809	0.3713
South Africa	1.0185	0.8565	1.6776	0.42230	0.3079	0.1816
Thailand	0.1609	0.4955	0.3654	0.7647	1.9196	2.038

Note: ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.

According to the t-statistic test results in Table 8, the dynamic bi-directional causality exists between contagion and *FDI* inflows since the null of non-causality is rejected in the case of Egypt, Chile, and Romania. It can also be observed that unidirectional causality occurs between contagion and *FDI* inflows for China, the Philippines, Colombia, Russia, Hungary, and Bulgaria. The results provide evidence of unidirectional causality running from the contagion to *FDI*s of China and Hungary. On the other hand, there is a unidirectional causality running from the *FDI*s of Colombia, Russia, and Bulgaria to the degree of contagion. However, it is evident that there is no causality between contagion and *FDI* inflows of other emerging countries (Argentina, Brazil, India, Indonesia, Mexico, Morocco, the Philippines, South Africa, and Thailand).

Our Granger causality results indicate a linkage between the contagion risk and *FDI* inflows in some emerging countries, which means that policymakers can rely on the lagged values of the contagion risk inflows as an indicator to forecast the *FDI* inflows to some emerging countries (China and Hungary). Thus, these results confirm the transmission of shocks from the U.S. crisis to some emerging countries. On the other hand, we also observe an interesting result that *FDI* inflows can be used as the indicator to forecast the contagion between the U.S. and Bulgaria, Chile, Colombia, Egypt, Romania, and Russia.

Therefore, these countries' policymakers can predict the contagion effect by considering the *FDI* inflows in their countries to prevent the spread of the crisis in the future.

Interestingly, we find weak evidence of the impact of contagion on *FDI* inflows across countries. We note that the Granger causality considers the lagged effect of the contagion. Thus, there would be very little impact of contagion on *FDI* inflows in emerging countries. With quarterly data used in this study, including the time lag that represents a huge amount of time, the impact of contagion on *FDI* inflows could proceed together within a quarter. Hence, there might exist the contemporaneous effect of contagion on *FDI* inflows.

5.4. The Impact of the U.S. Contagion on the FDI Inflows in Emerging Economies

The previous section focuses on examining the causality relationship between the contagion and *FDI* inflows using the statistical method without controlling for other determinants of *FDI* inflows. In addition, the Granger causality does not imply an actual causal effect but only examines whether two variables will interact with each other in the future or not [60]. In other words, this method neglects the contemporaneous effect of contagion (at lag 0) on *FDI* inflows. Thus, we finally complement the analysis by investigating the contemporaneous effect of contagion and economic determinants on *FDI* inflows within the regression framework. We would like to note that although Granger causality reveals a causality running from the *FDI*s of Bulgaria, Chile, Colombia, Egypt, Romania, and Russia to the degree of contagion, it does not indicate that the endogeneity problem (caused by reverse causality) occurs in our regression results.

The regression results for all countries are reported in Table 9. Considering our degree of contagion variable, we find a significant effect of contagion risk on *FDI* inflows in eight out of the 18 emerging countries, including Bulgaria, China, Colombia, Indonesia, Morocco, the Philippines, South Africa, and Thailand.

As expected, the sign of this variable is mainly negative in the cases of Bulgaria, Colombia, Indonesia, and South Africa, indicating that the U.S. contagion risk has made substantial negative contributions to the *FDI* inflows of these countries. This result is consistent with the explanation of Urata [61] and Ucal et al. [1]. Urata [61] mentioned that the financial crisis had a discouraging impact on *FDI* inflow as the macroeconomic performance became uncertain. Ucal et al. [1] revealed that the financial crisis affects the future foreign investment plan of the U.S. firm and thereby decelerating the *FDI* outflows to other countries. However, in the case of China and Morocco, the Philippines and Thailand, the U.S. contagion shows a significant positive influence on the *FDI* inflows. This result is consistent with the theory and approach of [62,63] and the findings of Hasli et al. [41]. According to Krugman [63], fire-sale transactions (extremely discounted prices) may occur during the crisis period. Although there was simultaneously a flight of short-term capital outflows and sell-offs of foreign portfolios during the crisis, there was an inward flow of foreign direct investment due to the reform of the foreign investment policy of the local government. He also mentioned that the reform of policy led to the abolishment of old policies, which deterred *FDI*, and the desperation for cash by local firms encouraged *FDI*. Thus, Multinational firms could respond to the attractive and liberalized *FDI* policies by acquiring companies and assets at fire-sale prices in emerging economies during the crises [56]. Moreover, Thu [62] explained that the crisis or contagion risk might provide the economic prospect to the emerging countries as it may force the government to reform the economic policy to attract more *FDI* to prevent the crisis.

Table 9. Estimation results of the contagion effect on *FDI* inflows in emerging countries.

Country	*Intercept*	Δln*Con*	Δln*GDPG*	Δln*Open*	Δln*Exchange*	Δln*CPI*
Argentina	0.0025 (0.0016)	−0.0014 (0.0013)	0.1152 *** (0.0332)	0.1583 *** (0.0126)	−0.1088 ** (0.0467)	0.0001 (0.0001)
Brazil	0.0011 ** (0.0004)	0.0003 (0.0005)	0.1679 * (0.0998)	0.0643 * (0.0341)	−0.0129 ** (0.0048)	−0.0005 ** (0.0002)
Bulgaria	−0.0018 ** (0.0007)	−0.0043 * (0.0022)	0.0123 *** (0.0031)	0.6255 *** (0.1291)	−0.0157 *** (0.0006)	−0.3153 *** (0.1243)
Chile	−0.0003 *** (0.0001)	−0.0002 (0.0007)	0.0463 ** (0.0261)	0.2600 *** (0.0085)	0.0407 (0.0666)	−0.0254 (0.0008)
China	−0.0003 (0.0004)	0.0393 *** (0.0141)	0.0644 *** (0.0213)	0.0002 *** (0.0001)	−0.0456 *** (0.0134)	−6.2671 *** (0.9269)
Colombia	−0.0013 *** (0.0002)	−0.0071 *** (0.0024)	0.0465 *** (0.0113)	0.3095 *** (0.0999)	0.0243 ** (0.0111)	−0.1041 (0.2383)
Egypt	0.1846 *** (0.0234)	−0.6734 (0.9832)	−0.3558 (1.245)	−0.1026 (0.1317)	0.7459 (1.7734)	−0.2235 (0.3492)
Hungary	−0.0105 *** (0.0015)	0.0105 (0.0204)	0.6251 *** (0.2327)	1.3551 *** (0.3434)	0.4829 *** (0.2142)	−0.1918 (1.0863)
India	0.0024 *** (0.0011)	−0.0013 (0.0021)	0.3304 * (0.1534)	−0.1865 (0.2344)	−0.1191 * (0.0674)	−1.6995 *** (0.5870)
Indonesia	0.0012 (0.0009)	−0.0013 * (0.0231)	0.1166 *** (0.0190)	0.6106 *** (0.1346)	−0.0073 (0.0242)	−0.0472 (0.0733)
Mexico	−0.00011 * (0.0005)	−0.0001 (0.0004)	0.2441 * (0.1298)	0.2014 *** (0.0543)	−0.0153 (0.3156)	−0.0015 (0.0009)
Morocco	0.0023 *** (0.0011)	0.0023 * (0.012)	−0.0301 (0.2225)	0.3003 ** (0.1271)	−0.0324 (0.0505)	0.0432 (0.2364)
Philippines	0.0010 ** (0.0005)	0.0004 * (0.0002)	−0.0053 (0.0711)	0.2336 *** (0.0123)	0.2565 *** (0.0805)	−0.0585 *** (0.0132)
Poland	0.0002)** (0.0001)	−0.0205 (0.0289)	0.1173 *** (0.0249)	0.5077 (0.6904)	0.0106 (0.0352)	−0.8980 *** (0.2335)
Romania	0.0002 * (0.0001)	−0.0006 (0.0012)	0.2400 * (0.1315)	−0.0354 *** (0.0086)	0.0036 *** (0.0011)	−0.3096 *** (0.1373)
Russia	0.0015 (0.0021)	−0.0216 (0.0608)	0.1831 *** (0.0521)	−1.1731 *** (0.3598)	−0.0592 (0.0578)	−0.3174 (0.4249)
South Africa	−0.0051 ** (0.0028)	−0.0043 ** (0.0022)	0.2015 (0.6133)	0.2203 *** (0.1034)	0.1199 (0.1076)	1.3934 (1.0761)
Thailand	−0.0005 *** (0.0002)	0.0025 *** (0.0001)	−0.5326 (0.6711)	−0.8639 ** (0.4135)	−0.7087 *** (0.3112)	−1.0763 * (0.5551)

Note: ***, **, and * indicate the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively. The parentheses () present the standard error.

Before closing the regression results discussion, it is worth highlighting the findings regarding the control variables included in the regressions. The estimated coefficients vary across countries. The *GDP* coefficient is significant in explaining the *FDI* inflows in most countries (except for Egypt, Morocco, the Philippines, South Africa, and Thailand). The estimated insignificant coefficients of the *GDP* growth of Egypt, Morocco, the Philippines, South Africa, and Thailand agree with the findings of [64]. A possible reason for this insignificance is that the impact on growth depending on the host country's income [65] and the productivity-enhancing benefits of *FDI* holds when a sufficient absorptive capability for advanced technologies is available to the host country [66]. Therefore, *FDI* inflows to these countries (with low technologies) are not important drivers to transfer technologies and support economic growth. Ndikumana and Sarr [67] confirmed that the overall gains from *FDI* inflows in employment and welfare were limited in low technology countries, particularly the African region.

We find supporting evidence that the higher trade openness has a positive effect on *FDI* inflows in Argentina, Brazil, Bulgaria, China, Colombia, Hungary, Indonesia, Mexico, Morocco, Philippines, Romania, and South Africa, suggesting that the higher openness can attract more *FDI* in these countries. These arguments are supported by the research of [41,48,68]. However, the trade openness coefficient turns out to be negative and significant in Romania, Russia, and Thailand. These results indicate that, although openness is a source of *FDI* attractiveness in some emerging countries, the marginal benefit from improved openness is somewhat negative for some countries. Liargovas and Skandalis [69] mentioned that the impact of trade openness and *FDI* inflows are very complex, depending on each country's characteristics. Thus, the interpretation needs to be careful. Raff [70] explained that trade openness policy might not attract *FDI* as the external equilibrium tariffs are too low to induce *FDI*, and there are multiple equilibria, and countries are stuck in one that does not support *FDI*. For the exchange rate, we find a negative coefficient for this variable for Argentina, Brazil, Bulgaria, China, India, and Thailand, and positive for Colombia, Indonesia, Hungary, the Philippines, and Romania, while the coefficients are insignificant for the remaining countries. This implies that an appreciation (depreciation) of the host country's currency led to a decrease (increase) in *FDI* inflows since it increases (decreases) the cost of capital investment. However, the effect of the exchange rate on *FDI* is still uncertain as the positive effect of the exchange rate is observed in some countries. Lily et al. [71] suggested that if the purpose of *FDI* is to serve the domestic market, then the *FDI* and trade are substitutes; thus, the host currency's appreciation could induce more *FDI* inflows due to the higher purchasing power of the host country consumers. Finally, regarding the inflation rate, an increase in this variable brings about a significant *FDI* decrease in Bulgaria, China, India, the Philippines, Poland, Romania, and Thailand.

6. Conclusions and Suggestions

FDI plays an essential role in the global economy, in particular the emerging economies. Consequently, investigating its determinants is important to attract more *FDI* inflows. One of the most interesting and effective determinants is crisis contagion. Therefore, this paper aims at capturing the main impact of contagion risk of the U.S. on *FDI* inflows in 18 emerging countries.

To measure the tail dependence as an indicator of the degree of contagion effect, we use the four time-varying copulas, namely Student-t, Clayton, rotated survival Gumbel, and rotated survival Joe copulas. The result shows that the dependence between the U.S. and emerging countries is more symmetric than asymmetric, indicating a strong integration between the U.S. and emerging economies in both boom and recession periods. The time-varying copula results show marginal fluctuations of tail dependence over a wide range of the study period, and these confirm the presence of dynamic contagion effects between the U.S. and emerging countries. We obtain some interesting results about the degree of contagion effect in both pre-and post-U.S. crises. It is evident that the contagion size gradually increases for all countries, except Thailand, the Philippines, Argentina, and Chile. This indicates that the contagion risk of the U.S. increased after the crisis period. As revealed by Patipaskul et al. [56] and Çepni et al. [57], the U.S. and emerging economies have become more integrated after the implementation of the QE policy and the low saving interest rate in the U.S. Therefore, there were substantial capital flows from the U.S. to many emerging countries.

Moreover, we further investigate the impact of the U.S. contagion risk on the *FDI* inflows to emerging countries using the Granger causality test and linear regression model. We come to the conclusion that there is a heterogeneity of causal relationships between the U.S. contagion and *FDI* inflows to emerging countries. Both unidirectional and bi-directional relationships between contagion risk and *FDI* inflows are found in the Granger causality tests. The results indicate there is a two-way relationship between *FDI* and contagion in three countries. In the one-way relationship case, contagion only Granger-caused *FDI* in two countries, whereas *FDI* only Granger-caused contagion in three countries. A possible reason for this heterogeneity results is the variations within countries or short-run interactions between the contagion-*FDI* nexus. Our estimation provided a weak lagged effect of the contagion. Thus, there might exist the contemporaneous effect of contagion on *FDI* inflows. Furthermore, the fact about *FDI* Granger-caused contagion in six countries (Bulgaria, Chile, Colombia, Egypt, Romania, and Russia) is meant as a policy implication for these countries to predict the contagion effect by considering their *FDI* inflows.

To examine the contemporaneous effect, we use linear regression analysis. The results show a significant contemporaneous effect of contagion risk on *FDI* inflows in eight out of the 18 emerging countries, including Bulgaria, China, Colombia, Indonesia, Morocco, the Philippines, South Africa, and Thailand, and, thus, the policymakers and government of these countries should be aware of the contagion risk right after it appears. On the other hand, we also observe an insignificant impact of contagion risk on *FDI* inflows in the other 10 countries. This finding provides an implication for the policymakers of these 10 countries that, as their countries have been immune to the crisis and are not hit hardest by the crisis or severe global turmoil, they need to remain using the current foreign investment policy and enhance their immunization, to lead to the realization of a sustainable *FDI* development.

Lastly, we identify implications for both policymakers and authorities in emerging countries. Our results could help them find out whether their countries achieve sustainable development in their foreign direct investment and whether the U.S. contagion risk contributes more problems to the stability of the *FDI*. Furthermore, according to the control variables' results, the economic growth or market size and trade openness significantly impact the *FDI* attractiveness of a host country; that is why a host country with a higher growth rate of *GDP* and lower trade restriction will attract more *FDI*. Despite all the empirical developments performed in this study, some limitations remain.

Indeed, in analyzing the impact of contagion risk on *FDI* inflows in emerging countries, the social components, infrastructures, and technologies should be considered as the potential factors. Thus, these variables are also suggested for consideration to determine fully the factors affecting the *FDI* inflows. Moreover, as we observe the structural change in the dynamic tail dependence or contagion risk (Figure 1), further study may consider using the Markov switching time-varying copula [13] to measure the tail dependence as this model allows us to investigate the structural change in the contagion risk.

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