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# Measuring financial market risk contagion using dynamic MRS-Copula models: The case of Chinese and other international stock markets

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ABSTRACT

Considering the asymmetric dependency structure and regime switching process, we construct the dynamic Markov Regime Switching Copula (MRS-Copula) models to measure the financial risk contagion. The dynamic MRS-Copula models consist of the marginal model and dynamic MRS Rotated-Gumbel function, and they are examined by the goodness-of-fit test method. Using the dynamic MRS-Copula models, we calculate the daily lower tail dependency by adopting the international stock market index data from January 1997 to June 2015, and provide evidence of financial risk contagion effects between Chinese stock market and other international stock markets after the reform of the RMB exchange rate system in China, and this is particular the case after in the U.S. subprime mortgage crisis and the European debt crisis. When conducting robust tests with weekly and monthly data, the empirical result basically holds. As for the financial risk contagion channels in Chinese stock market, the fundamental economic linkages play a more important role than liquidity, information and other factors.


## 1. Introduction

The modern international stock markets are highly interdependent with each other. Despite the integration of global financial markets facilitating portfolio management, the financial risk or crisis could spread from one market to another in a very short time. So it is important to measure the risk contagion degree of the financial market for both academicians and practitioners.

Scholars have used different definitions, such as comovement, interdependence, volatility spillover and risk contagion to study the risk transmission of the financial markets. King and Wadhwani (1990), Baig and Goldfajn (1999), Barberis et al. (2005), Huyghebaert and Wang (2010), Hwang et al. (2013), and Aloui and Hkiri (2014) focus on the co-movement of the financial markets. Awokuse et al. (2009), Zhu et al. (2014), and He et al. (2015) study the financial market interdependence, and stress on whether a country's financial market is influenced by other international financial markets. While Mensi et al. (2013) and Alotaibi and Mishra (2015) detect the volatility spillover effects to study the financial risk contagion. Dornbusch et al. (2000), Forbes and Rigobon (2002), and Morales and Andreosso-O'Callaghan (2012) propose that contagion is a significant increase in cross-market linkages after a shock to an individual country (or group of countries). Durante and Foscolo (2013) consider contagion as a significant increase in co-movements of prices and quantities across markets, conditional on a crisis occurring in one market or group of markets. Although the definitions of co-movement, interdependence and volatility spillover are suitable to investigate the financial market interaction, it is difficult to identify the financial crisis period and the time when the contagion occurs. However, the definition based on correlation coefficients can solve this problem. By judging the decline and increase of correlation coefficients, the risk contagion period can be clearly identified. Thus, in our paper, we take the correlation coefficients among different markets as the basic indicators to detect the financial risk contagion effects, and the financial risk contagion occurs when the correlation between stock market significantly increases.

Previous works have applied multivariate GARCH models, conditional probability test and co-integration test methods to obtain the linear correlation or dependency structure of different markets (Bae et al., 2003; Bekaert and Wu, 2000; Hong et al., 2004). Their empirical results show that the linear correlation coefficient in crisis period is greater than that of normal period. Longin and Solnik (1995) study the dependency level changes among international equity markets during 1960–1990, and find the empirical evidence of crisis contagion among international stock markets. Hong et al. (2004) analyzes the extreme risk spillover effects, reporting that while the risk spillover effects are significant it existed among Chinese A shares market and other stock markets. Sibel's (2012) findings support the evidence of contagion during U.S. subprime crisis for most of the developed and emerging countries. In the research of Wang (2013), the evidence is found that Chinese stock market brings more contagion risk to the Vietnamese market when compared to the U.S. stock market by using a bivariate EGARCH model of dynamic conditional correlation coefficients.

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With the development of the statistic methods, scholars gradually find the drawbacks of the linear correlation or dependency structure calculated by the traditional models. Firstly, most of the linear correlations are not time-varying. Secondly, it is difficult to investigate the asymmetry dependency of different markets by using the linear correlation. Thirdly, the linear correlation has poor ability to capture the extreme downside risk spillover. To deal with the above limitations, scholars develop the Copula methods to describe the dynamic and asymmetric dependency structures. As Copula isolates the dependence pattern from the marginal distributions, it is easy to acquire the different dependency structure and contagion effects (Ang and Chen, 2002; Chollete et al., 2009; Das and Uppal, 2004; Longin and Solnik, 2001; Patton, 2006a, 2006b; Peng and Ng, 2012; Wang and Liu, 2011; Wen et al., 2012; Wu and Zhang, 2010). By applying Copula methods, previous works figure out the asymmetric dependency of the international financial markets, which indicates that dependency between the stock markets in the crisis period is higher than that of the normal period. Thus, in our paper, we apply the tail dependency coefficient instead of linear correlation to study the financial risk contagion between Chinese stock market and other international stock markets.

Meanwhile, some scholars (Dueker, 1997; Hamilton and Susmel, 1994; Hess, 2003; Lamoureux and Lastrapes, 1990) recognize the unstable state of the stock market, and argue that the Markov Regime Switching (MRS) model is more precise in modeling time variation of stock market return distribution. More recently, Guo et al. (2011) investigate the contagion among the stock market and other financial markets. Miao et al. (2013) insist that correlation model with regime-switching method can explicitly point out structure changes for time series variables. Lin et al. (2014) find that the Markov Regime Switching models can explain the dynamics of S&P 500 stock index.

Considering the asymmetric dependency, tail dependency and regime switching process, we construct dynamic Markov Regime Switching Copula models to measure the financial risk contagion. There are several advantages to adopt this approach. First, the crisis and calm period of the financial market is objectively identified by judging the smooth probability. Second, by using this approach, it is more efficient to capture the dynamic and asymmetric dependency structures among different markets. Third, instead of the normal distribution, skewed-t and generalized error distribution are applied to model the fat-tailed marginal distribution. The above advantages of the dynamic MRS-Copula models allow us to investigate the financial risk contagion in a more precise way. Taking the Chinese stock market and other international stock markets as the empirical samples, our results show that the dynamic MRS-Copula models can clearly distinguish the different states of the risk contagion, and the lower tail dependency gradually increases after the reform of RMB exchange rate system, and dramatically rises after U.S. sub-prime mortgage crisis in 2007. Later, the lower tail dependence stays at a high level until 2013, and this high level period also covers the European debt crisis. Therefore, our empirical study provides evidence of financial risk contagion between Chinese stock market and other international stock markets.

The rest of the paper is organized as follows. In Section 2, we build the dynamic MRS-Copula models, and we specify the marginal model, the Copula function, model test method and the indicator of financial risk contagion. In Section 3, we report the empirical results. In Section 4, we conduct robustness test by using monthly and weekly return data. Finally, conclusions are stated in Section 5.

## 2. Dynamic MRS-Copula model

### 2.1. Marginal model specification

Traditional GARCH models are estimated under the conditional normality assumption to measure the correlation of time series data. However, this assumption is rejected by the existing literature (Longin and Solnik, 2001; Hong et al., 2004; Patton, 2006b; Peng and Ng, 2012, etc.). By contrast, the use of Copula function allows us to consider the marginal distributions and the dependence structure both separately and simultaneously, thus the non-normality of the joint distribution and the dependency structure can be modeled more appropriately.

For modeling the marginal distribution, it is generally assumed that financial asset volatility is time-varying and clustered, and TGARCH model can well describe these volatility characteristics of financial assets. Therefore, we apply the AR($p$)–TGARCH($p$, $q$) as the marginal models of asset returns to construct the Copula models. According to Nelson (1991), we suppose that the standard residual complies with the skewed-t distribution or generalized error distribution (GED). The model is given by:

$$r_t = \mu + \sum_{i=1}^{p} \rho_i r_{t-i} + \varepsilon_t \tag{1}$$

$$h_t = c + \sum_{i=1}^{p} \varphi_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{t-j} + \gamma I(\varepsilon_t<0)\varepsilon_t^2. \tag{2}$$

Here, $z_t = \varepsilon_t/\sqrt{h_t} \sim \text{skewed}-t(\upsilon,\eta)$ or $z_t \sim \text{GED}(\varsigma)$, $\varepsilon_t$ is the residual of the return, and $h_t$ is the conditional variance. $z_t$ refers to independent and identically distributed standard residual that complies with skewed-t distribution or generalized error distribution. $k_{t-1} = 1$ when $\varepsilon_{t-1}$ is negative, otherwise $k_{t-1} = 0$. The density function of the skewed-t distribution is:

$$\text{skewed}-t(z|\upsilon,\eta) = \begin{cases} bc\left(1+\dfrac{1}{\upsilon-2}\left(\dfrac{bz+a}{1-\eta}\right)^2\right)^{-\upsilon+1/2}, & z<-\dfrac{a}{b} \\ bc\left(1+\dfrac{1}{\upsilon-2}\left(\dfrac{bz+a}{1-\eta}\right)^2\right)^{-\upsilon+1/2}, & z\geq-\dfrac{a}{b} \end{cases}. \tag{3}$$

The values of $a$, $b$, and $c$ are defined as:

$$a = 4\eta\frac{\upsilon-2}{\upsilon-1}, b = 1+3\eta^2-a^2, c = \frac{\Gamma(\upsilon+1/2)}{\sqrt{\pi(\upsilon-2)}\Gamma(\upsilon/2)}$$

where $\upsilon$ is the freedom degree parameter and $\eta$ is the asymmetry parameter. These two parameters are restricted to $4 < \upsilon < 30$ and $-1 < \eta < 1$. A negative $\eta$ indicates that the distribution is left skewed, which suggests that there is a greater probability of negative returns. Thus, the asymmetric and fat-tailed features of the asset returns can be well defined by skewed-t distribution. If the distribution of the asset returns shows a significant asymmetry characteristic, then the assumption that the standardized residuals obey the skewed-t distribution is appropriate, otherwise, the generalized error distribution is applied in the process of modeling. The generalized error distribution is advantageous on adjusting the parameter $\varsigma$ to fit different distribution forms. The density function of GED can be expressed as:

$$f(z,\varsigma) = \frac{\varsigma \cdot \exp\left[-\dfrac{1}{2}\left|z/\lambda\right|^{\varsigma}\right]}{\lambda \cdot 2^{\left[\frac{\varsigma+1}{\varsigma}\right]} \cdot \Gamma\left(\dfrac{1}{\varsigma}\right)} \tag{4}$$

where $\lambda = [2^{-2/\varsigma} \cdot \Gamma(1/\varsigma)/\Gamma(3/\varsigma)]^{0.5}$, $\Gamma(\cdot)$ is the gamma function and $\varsigma$ is a scale parameter, or degrees of freedom to be estimated endogenously. For $\varsigma = 2$, the GED yields the normal distribution, while for $\varsigma = 1$ it yields the Laplace or, double exponential distribution.