Research on the Modeling of Crisis Contagion Effect of Stock Market Based on Spatial Perspective

Cao Danting, Wen Lu

School of Economics and Management, Yuzhang Normal University, Nanchang, Jiangxi, China

Keywords: Clayton-copula, Spatial correlation, Crisis contagion effect

Abstract: The interdependence of stock markets is affected not only by geographical proximity, but also by economic similarity. In order to adapt to the multi-dimensional spatial effect characteristics under the background of crisis contagion, this paper aims at the phenomenon that the existing spatial econometrics weight matrix is insufficient, and proposes to use Clayton-Copula connection function to construct Kendall rank correlation coefficient to define the weight matrix as the carrier of crisis contagion. By constructing the distance attenuation spatial weight matrix, it helps to determine whether the non-traditional economic similarity can satisfy the spatial effect in the context of crisis contagion.

1. Introduction

With the acceleration of economic globalization, the correlation and linkage between financial securities markets in different countries become more and more frequent. The limitation of single research on the changes of financial securities market in a certain country or region is increasingly obvious. On the one hand, the volatility of a single financial market will have an impact on the financial markets of neighboring regions, leading to chain fluctuations of financial markets in different regions (Bauwens and Rombouts 2006), forming a “ripple effect”. On the other hand, due to the frequent economic and trade exchanges between countries, the macroeconomic policies of a single country, especially monetary policy, will not only affect the local financial system, but also the financial system of neighboring countries (Asgharian, Hess et al. 2013). The study of this paper will enrich the literature on spatial contagion effect under the situation of economic prosperity and economic depression. On the other hand, this project uses nonparametric estimation Copula, combines spatial contagion method with time series model (multivariate GARCH model), calculates Spearman rank correlation coefficient, and constructs a new spatial weight matrix. The Kendall rank correlation coefficient is used as the measure of dependence degree, which reflects the tail dependence relationship between stock markets, and measures the nonlinear and asymmetric tail correlation between stock markets which were ignored in previous studies. It provides a new idea for the research of spatial measurement in financial markets.

2. Research and Development Trend of Stock Market under Spatial Effect

A large number of studies have shown that there is a significant spatial effect on the returns or returns of stock markets in various countries. Fernández-Avilés and Montero (2012) studied the return rate of 17 global stock markets based on the bilateral distance measurement of geographical and economic distance of stock markets of various countries. It was found that compared with the spatial linkage of poor geographical distance, economic distance more accurately revealed the dependence of world financial market. Pan Rongcui and Zhang Xin (2012) studied from the perspective of macroeconomic impact on stock index, and reached similar conclusions. Borovkova (2012) used the inverse distance between stock market cities, GDP and market to construct a spatial matrix, and through the optimized GARCH (1,1) model, revealed the peak degree in the square of return rate. On the basis of S-CAPM theory, Zhang Yuhua and song Jixuan (2016) studied the influencing factors of stock return by using quarterly spatial panel data, and found that stock return was affected not only by geographical and economic distance, but also by spatial differences among

  DOI: 10.25236/icembe.2020.013

different industries. Ferreira et al. (2017) used adaptive multifractal elimination Volatility Analysis (AMF-DFA) and adaptive multifractal to conduct cross correlation analysis (AMF-DXA) in the stock market. The results show that the strongest relationship is between emerging markets and between emerging markets and border markets. However, the above research is mainly based on the daily financial market operation and data, and fails to consider the spatial correlation and contagion of stock market volatility when the market appears extreme or crisis, which provides an opportunity for the research of this topic.

3. Research and Development Trend of Crisis Contagion in Stock Market

Longin and Solnik (1995) used the monthly excess returns of major European stock markets from 1970 to 1990 as samples to study the correlation between stock markets and their mechanism. The study found that economic fundamentals are the main reasons for the gradual increase in correlation among samples, and the impact of correlation on financial crisis is also increasing. Asgharian and Hess (2013) studied the spatial effects of the stock markets of the dominant countries in the United States, the United Kingdom and Japan on other countries, and further proved the impact of Thailand market on the financial markets of neighboring countries during the Asian financial crisis. Zhu Junjun and Xie Shiyu (2012) used MCMC estimation spatial Probit panel model to study the spatial correlation of contagion effect of sovereign debt crisis among countries. Wang et al. (2017)] proposed a multi-scale correlation contagion statistics to study how the stock market spread from the United States to other six countries and BRICs during the global financial crisis (GFC). It is found that the cross market linkages between the United States and selected countries are interactive. On the time scale, the stock market spread during GFC depends on the affected countries and time scale. For example, it took 50 days for the crisis to spread from the United States to Japan, China and Brazil. However, in the application of spatial measurement, several commonly used weight matrix setting methods are mainly used, including absolute geographical distance and economic development distance. However, under the background of frequent financial crisis, financial information spreads rapidly around the world almost instantaneously. Using general weight setting such as geographical distance, in the case of extreme financial events, the research on the spatial linkage of global stock market may lead to difference from estimation.

4. Model building

Dynamic spatial panel lag model SAR:

$$\mathrm{Y}_{\mathrm{it}} = \tau \mathrm{Y}_{\mathrm{i,t\text{-}1}} + \delta \mathrm{WY}_{\mathrm{it}} + \eta \mathrm{WY}_{\mathrm{i,t\text{-}1}} + \mathrm{X}_{it}\beta_1 + \mathrm{u}_i + \varepsilon_{it} \tag{1}$$

Dynamic spatial panel Durbin model SDM:

$$\mathrm{Y}_{\mathrm{it}} = \tau \mathrm{Y}_{\mathrm{i,t\text{-}1}} + \delta \mathrm{WY}_{\mathrm{it}} + \eta \mathrm{WY}_{\mathrm{i,t\text{-}1}} + \mathrm{X}_{it}\beta_1 + \mathrm{WX}_{it}\beta_2 + \mathrm{u}_i + \varepsilon_{it} \tag{2}$$

Y_{it} is the daily rate of return of asset i at time, where i represents different assets(i=1,…,N),t represents different periods(t=1,…, T).For a series of factors affecting the rate of return,,W is a spatial weight matrix reflecting the strength correlation between asset i and asset j. Parameter τ, δ, η are the lag values of explained variable $Y_{i,t-1}$ in time, The lag value of explained variable $W*Y_{it}$ in space and the response parameters of the lag values of the explained variables $W*Y_{i,t-1}$ in space and time. The coefficient τ reflects the dynamic characteristics of the rate of return. δ is the spatial correlation coefficient, its sign and significance directly reflect whether there is spatial interaction effect in the daily return rate of different assets. $\delta>0$, it shows that there is a positive interaction in the distribution of return rate; otherwise, it is a reverse interaction; u_i is the fixed space effect of assets, ε_{it} is obey mean value ,The variance σ^2 is a random error vector of independent and identically distributed. The study of this model can be seen in(Yu, Jong et al. 2008, BouayadAgha and Védrine 2010, Lee and Yu 2014).

(Lee and Yu 2010) believe that the fixed effect model is more robust and simpler in calculation than the random effect model. Based on the research, this paper considers the fixed effect of spatial autoregressive model.

According to (Yu, Jong et al. 2008), this model is estimated by using the quasi maximum likelihood (QML) estimator. Firstly, intra group dispersion transformation was performed to remove individual effects, and then MLE was estimated. Details:

$$\mathrm{Y_{it}} = \tau \mathrm{Y_{i,t\text{-}1}} + \delta \mathrm{WY_{it}} + \eta \mathrm{WY_{i,t\text{-}1}} + \mathrm{X}_{it}\beta_1 + \mathrm{WX}_{it}\beta_2 + \mathrm{u}_i + \varepsilon_{it}$$

Definition: $\mathrm{S}_i \equiv \mathrm{S}_i(\delta) = \mathrm{I}_i - \delta W$

Suppose $\mathrm{S}_i(\delta)$ is reversible, that: $A_i = \mathrm{S}_i^{-1}(\tau\,\mathrm{I}_i + \eta W)$

So: $$\mathrm{Y_{it}} = A_i \mathrm{Y_{i,t\text{-}1}} + \mathrm{S}_i^{-1}\mathrm{X}_{it}\beta_1 + \mathrm{S}_i^{-1}\mathrm{WX}_{it}\beta_2 + \mathrm{S}_i^{-1}\mathrm{u}_i + \mathrm{S}_i^{-1}\varepsilon_{it}$$

Step 1, use mean removed variable Y_{it} and regression equation of X_{it} to eliminate the spatial fixed effect u_i , the transformation form of this removing mean is:

$$Y_{it}^{*} = Y_{it} - \frac{1}{T}\sum_{t=1}^{T} Y_{it},\ Y_{i,t-1}^{*} = Y_{i,t-1} - \frac{1}{T}\sum_{t=1}^{T} Y_{i,t-1},\ \mathrm{X}_{it}^{*} = \mathrm{X}_{it} - \frac{1}{T}\sum_{t=1}^{T} X_{it}$$

Step 2, using MLE estimation, the log likelihood function of the sample is as follows:

$$\ln L(\tau,\ \delta,\ \eta,\ \sigma^2) = -\frac{nT}{2}\ln 2\pi - \frac{nT}{2}\ln\sigma^2 + T\ln\left|\mathrm{S}_i(\delta)\right| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\ \sum_{t=1}^{T}\varepsilon_{it}^{*\prime}\varepsilon_{it}^{*}$$

Here

$$\varepsilon_{it}^{*} = \mathrm{S}_i(\delta)Y_{it}^{*} - \tau\mathrm{Y}_{\mathrm{i,t\text{-}1}}^{*} - \eta\mathrm{WY}_{\mathrm{i,t\text{-}1}}^{*} - \mathrm{X}_{it}^{*}\beta_1 - W\mathrm{X}_{it}^{*}\beta_2$$

Order $\beta_2 = 0$; equation (3) is the same as above

In addition, (Elhorst 2010) shows that at a specific time point, the partial derivative matrix of the expected value of Y corresponding to the kth explanatory variable in X from spatial unit 1 to spatial unit n can be written as:

$$\left[\frac{\partial \mathrm{E}(Y)}{\partial x_{1k}} \cdots \frac{\partial \mathrm{E}(Y)}{\partial x_{Nk}}\right]_t = (\mathrm{I} - \delta W)^{-1}(\beta_{1k}\mathrm{I}_N + \beta_{2k}W) \tag{5}$$

These partial derivatives represent the effect of one unit change of a specific explanatory variable in a specific spatial unit on the explained variables of all other spatial units in a short period of time. Similarly, its long-term effects can be written as follows:

$$\left[\frac{\partial \mathrm{E}(Y)}{\partial x_{1k}} \cdots \frac{\partial \mathrm{E}(Y)}{\partial x_{Nk}}\right]_t = \left[(1-\tau) - (\delta+\eta)W\right]^{-1}(\beta_{1k}\mathrm{I}_N + \beta_{2k}W) \tag{6}$$

In equations (5) and (6) $\beta_{2k} = 0$ corresponds to the effect of SAR; $\beta_{2k} \neq 0$ corresponds to the effect of SDM;

Order

$$V_{kt} = \left[(1-\tau)-(\delta+\eta)W\right]^{-1}\left(\beta_{1k}\mathrm{I}_N + \beta_{2k}W\right)$$

So, $\overline{M}(k)_{direct}, \overline{M}(k)_{indirect}, \overline{M}(k)_{total}$ represent the long-term average direct effect, long-term average indirect effect and long-term average total effect of the change of model variable X_k:

$$\overline{M}(k)_{direct} = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{i=j}^{N} V_{ij,kt}}{N}$$

$$\overline{M}(k)_{indirect} = \sum_{t=1}^{T}\frac{\sum_{i=1}^{N}\sum_{i\neq j}^{N} V_{ij,kt}}{N(N-1)}$$

$$\overline{M}(k)_{total} = \overline{M}(k)_{direct} + \overline{M}(k)_{indirect}$$

Order $\tau = 0, \eta = 0$ represent the short-term average direct effect, short-term average indirect effect and short-term average total effect of the change of model variable X_k.

5. Summary

In recent years, the global stock market has experienced many dramatic changes. It is becoming more and more common for individuals to choose diversified portfolio not only for investment purposes but also for risk aversion. Therefore, cross market linkages are strengthened, and spatial linkages and their transmission channels have an impact on the optimal allocation strategy of portfolio management.

Although the traditional volatility spillover model is completely based on time series analysis, we propose a spatial econometric method. This is because the spatial weight matrix and spatial lag operator can reduce N×N unknown coefficients (where N is the number of spatial elements) to only one parameter - Spatial correlation coefficient. Therefore, this model is very suitable for measuring the spatial interaction between more spatial units or regions, because compared with multivariate GARCH method, spatial correlation technique can increase degrees of freedom and avoid multicollinearity.

In addition, the interdependence of stock markets is affected not only by geographical proximity, but also by economic similarity. In order to adapt to the multi-dimensional spatial effect characteristics under the background of crisis contagion, this paper aims at the phenomenon that the existing spatial econometrics weight matrix is insufficient, and proposes to use Clayton-Copula connection function to construct Kendall rank correlation coefficient to define the weight matrix as the carrier of crisis contagion. By constructing the distance attenuation spatial weight matrix, it helps to determine whether the non-traditional economic similarity can satisfy the spatial effect in the context of crisis contagion.

Acknowledgment

Science and technology research project of Jiangxi education department, No. GJJ191216.

References

[1] Abate, G. D. (2015). “On the Link between Volatility and Growth: A Spatial Econometrics Approach.” Spatial Economic Analysis: 1-19.

[2] Durante, F. and E. Foscolo (2013). “An Analysis of the Dependence Among Financial Markets by Spatial Contagion.” International Journal of Intelligent Systems 28(4): 319-331.

[3] Eckel, S., G. Löffler, A. Maurer and V. Schmidt (2009). “Measuring the effects of geographical

distance on stock market correlation." Journal of Empirical Finance 18(2): 237-247.

[4] Sharpe, W. F. (1964). "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." The Journal of Finance 19(3): 425-442.

[5] Tam, P. S. (2014). "A spatial–temporal analysis of East Asian equity market linkages." Journal of Comparative Economics 42(2): 304-327.